COMPUTATIONAL ANALYSIS OF TECHNOLOGICAL INNOVATION IN COMPLEX ENTERPRISE SYSTEMS

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COMPUTATIONAL ANALYSIS OF TECHNOLOGICAL INNOVATION IN COMPLEX ENTERPRISE SYSTEMS

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To my parents and family,

and to my beloved wife Jean Ho.

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GLOSSARY

AAR	Average Abnormal Return, p. 156.
CAAR	Cumulative Average Abnormal Return, p. 141.
CAR	Cumulative Abnormal Return, p. 155.
CPI	Consumer Price Index, p. 148.
CPU	Central Processing Unit, p. 72.
CRSP	Center for Research in Security Prices, p. 147.
CTMC	Continuous-Time Markov Chain, p. 183.
CUSIP	Committee on Uniform Securities Identification Procedures, p. 34.
DID	Difference-in-Differences, p. 10.
DTMC	Discrete-Time Markov Chain, p. 183.
FE	Fixed Effect, p. 116.
HHI	Herfindahl-Hirschman Index, p. 81.
ICT	Information and Communications Technology, p. 22.
IP	Intellectual Property, p. 51.
ISP	Internet Service Provider, p. 51.
MSCI	Morgan Stanley Capital International, p. 147.
NPD	New Product Development, p. 140.
OEM	Original Equipment Manufacturer, p. 34.
OLS	Ordinary Least Square, p. 9.
OS	Operating System, p. 72.
PDA	Personal Data Assistant, p. 72.
RAM	Random Access Memory, p. 74.
SEC	U.S. Securities and Exchange Commission, p. 31.
SIC	Standard Industry Classification, p. 17.
VIF	Variance Inflation Factor, p. 88.
WRDS	Wharton Research Data Service, p. 147.

SUMMARY

Technological innovation in complex enterprise systems requires coordinated interplay between a heterogeneous set of industrial players. The complexity in how firms form relationships with each other perplexes the decision-making processes for individual players when they explore the technological search space in order to achieve breakthrough innovation. Building upon the existing literature on business ecosystem, interfirm alliance, new product development, and technology management, we explore the interplay between technological innovation and interfirm relationship as well as the alliance formation patterns in the business ecosystem context. We start with providing a macroscopic perspective on the information and communication technology ecosystem, followed by in-depth empirical investigations in the mobile handset industry. We employ network visualization, sequence clustering, and organizational simulation methodologies for the macroscopic analysis. Our microscopic analysis borrows methodologies from econometrics including regression analysis, difference-in-differences estimation, and event study. Our results propose an effective way to visualize the whole industrial ecosystem and show how the enterprise system has transformed over time. The results of the microscopic analyses show how interfirm relationship shapes technological innovation and how technological innovation is materialized in firm value. Lastly, we present an integrated computational framework to infer alliance formation strategy. We contribute to the literature by providing generative methods and empirical evidences that accommodate a more complete view of the innovation process in the business ecosystem setting. The dissertation concludes by suggesting directions for future research and highlighting implications for research and practice in the area of technological innovation in the business ecosystem.

CHAPTER I

INTRODUCTION

1.1 Motivation

The tool that people used in an era has defined the era from the stone age to the information age. Human history has evolved with the technological advancements of the tools. A sufficiently disruptive advancement opens up a new era, while a plethora of incremental improvements accumulated within an era enables transformation (Christensen, 2013). Tools, instantiated in the form of products and services around us, represent the outcome of the underlying innovation processes and comprise the collective wealth of humanity (Beinhocker, 2006). Sitting atop this accumulated wealth, we are literally observing the era of technological innovation. Media highlights new products and services every day and people crave them at a rapid pace. Every product and service around us—automobile, aircraft, phone, computer, and even web service—is getting better and better in a more nuanced way. Understanding the underlying process of innovation has attracted a great deal of attention and effort from the research community since Schumpeter (1942) formulated the concept of "creative destruction" as a general innovation process.

Among many theoretical attempts, Henderson and Clark (1990) provide a renowned conceptual framework with which we understand the process of innovation today. Before this study, technological innovation was viewed in dichotomies: incremental and radical innovation. The authors break down the lens to view the innovation outcomes into two dimensions. One dimension is whether the core component has changed and the other dimension is whether the linkages among components have changed. Based on this framework, they introduce two new concepts of innovation. Modular innovation refers to innovation that replaces the core component in the product or the service, while architectural innovation refers to innovation that rewires existing components in a different way. This framework is particularly useful as the architecture of a single product or a single service becomes increasingly complex. Automobiles or aircrafts are good examples of complex products. By complex we mean that components of a product or a service are interdependent to deliver the desired value. Because of this interdependency, the way components are connected to each other is as important as individual performance of a component to achieve innovative outcomes. Although their intention is not to divide every innovation into four categories, their framework achieves their intent by highlighting the importance of configuration among components for innovation. This innovation framework is general enough to explain possible innovation directions for a simple object like a light bulb as well as a complex object like a modern automobile.

Today, we are facing at least two driving forces that call for updating our current conceptualization of the innovation process. The first transformative force is that not only product/service components are interdependent but also companies themselves are interdependent horizontally. Traditionally, interdependence between components can be viewed as hierarchical supply chain structure (Luo et al., 2012). For instance, an automobile consists of a myriad of components and parts such as engine, tire, frame, and electronic control unit. The automobile manufacturer is responsible to ensure components work in a coordinated manner to achieve desired performance. However, today's value creation process often involves horizontal cooperation between independent companies. For instance, Google or Facebook does not provide all possible services themselves. Rather, they create value for end users by allowing third-party entities to create and deliver services through their service (Basole and Rouse, 2008). This open structure of innovation exists not only for service companies but even for brick-and-mortar companies, which is conceptualized as "open innovation" in Chesbrough (2003). Even in supply chain management, the structure to manage is shifting from a linear sequence to a network (Bellamy et al., 2014; Basole and Bellamy, 2014). While the recent business ecosystem literature attempts to provide a holistic perspective on the interconnectedness and interdependence among firms taking different roles (Iansiti and Richards, 2006; Moore, 1996), the technological innovation literature has not incorporated this necessary new perspective.

The second driving force is the wide availability of digital platforms. The importance of seizing hegemony in digital platforms has been recognized dating back to when Microsoft became a de facto monopoly for operating system in the personal computer industry by the mid-'90s. Since then, a number of theoretical and empirical studies investigate the nature of platform-based competition in multi-sided markets (Rochet and Tirole, 2003, 2006; Armstrong, 2006; Wilbur, 2008; Weyl, 2010). One of the key findings from the development of this literature was to recognize the importance of managing network effect (Uzzi, 1996). We witness abundant examples of successful platform-based businesses from flourishing web services and the ecosystem. In spite of the paramount importance of platforms across the board, the technological innovation literature has not consolidated the roles and effects of digital platforms. Platforms are important in its own right, but they can potentially enable and disable certain trajectories of technological evolution in products and services.

This dissertation addresses this call to update the innovation framework in the business ecosystem context and consider the presence of digital platforms. Our research context focuses on the ICT ecosystem, where hardware equipment manufacturers, hardware component manufacturers, telecommunications service providers, software developers, and media companies coexist and depend on each other to create and deliver value to end users. In the ICT ecosystem, innovative products and services are outcomes of the underlying new product development process shaped by strategic cooperation and competition. Unless a product of interest is simple nuts and bolts, a firm inevitably faces strategic choice between cooperation and competition. Each firm's choice affects another's, so the industrial ecosystem is interconnected via various feedback loops. A complex product or service is likely an output of orchestration among firms with specialization in different areas of expertise. In addition to cooperation, firms of each type compete with each other. The competition drives firms to keep working on offering more innovative product at a competitive cost than their competitors.

To perform in-depth analysis on product innovation, we zoom into the mobile handset industry from the broader ICT ecosystem. A mobile handset is an output from the collaboration of at least three types of players: hardware manufacturer, service provider, and software developer. These players co-create the value delivered through mobile handsets. At the same time, firms within each type compete against each other. Samsung competes with HTC in the manufacturer realm, AT&T with Verizon in the network carrier arena, and Apple with Google in the digital platform area. Since manufacturers have to deal with their suppliers and software platforms source contents from content providers, this triadic structure is embedded in the broader ecosystem context. Figure 1 illustrates the relationship among the triad in the ICT ecosystem. Based on these two macroscopic and microscopic contexts, we describe the evolution of the ICT ecosystem, advance the technological innovation theory incorporating digital platforms, and investigate the interaction between inter-firm relationship and product innovation.

The three parties in the middle row play the central role in the ecosystem. Manufacturers assemble a final product using its supply chain network to procure parts. Network carriers in this context are service providers that transform a phone from a plastic box to something useful. Lastly, platform developers are software companies that build software that runs on the product. Sometimes, a single firm could play

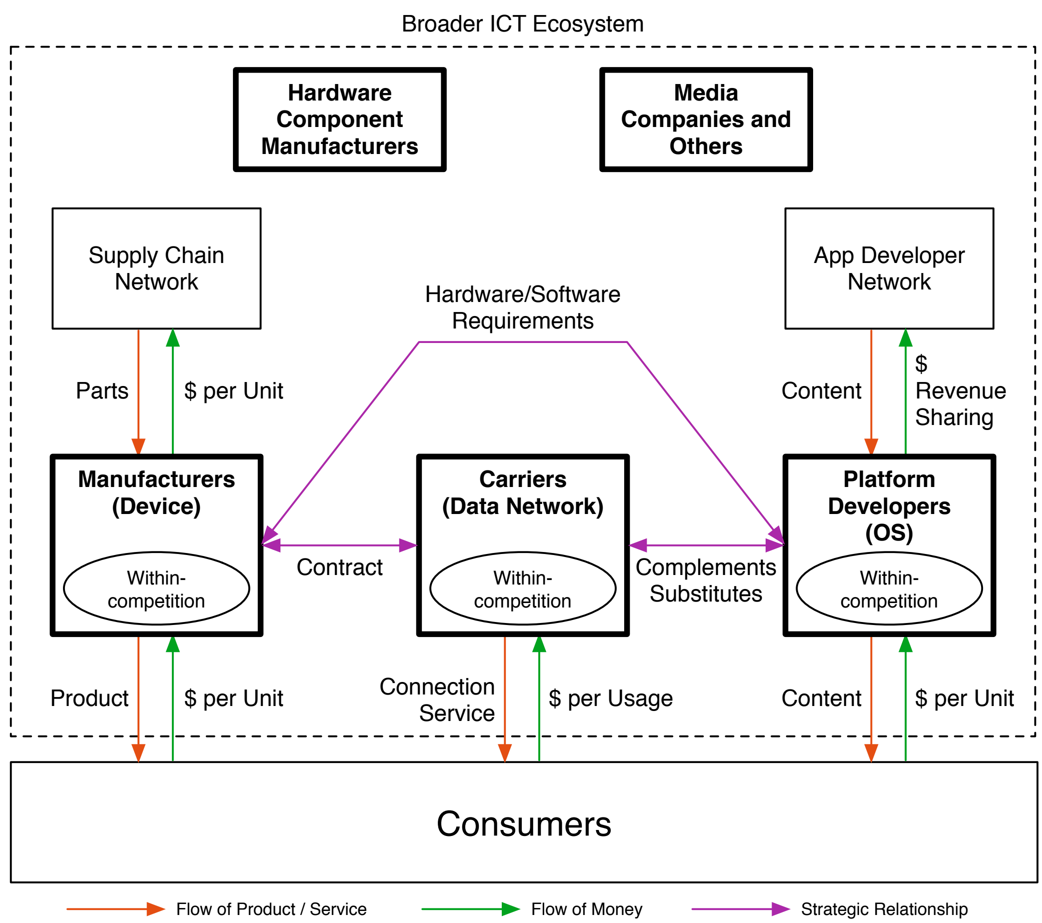


Figure 1: Schematic Illustration of the Mobile Handset Industry Embedded in the ICT Ecosystem

both roles of manufacturer and platform developer. Apple epitomizes such a case. These days, the platform developers have grown a network similar to the supply chain network of manufacturers: application developer network. While the vertical relationship can be characterized as one party purchasing goods and/or service from the other, the relationship among the central players is not. These central firms do not have monetary relationship but strategic relationship. Manufacturers need to conform the platform developers' hardware requirements. Platform developers offer software functionalities that could potentially harm the profitability of the service providers' value propositions. Manufacturers cannot sell any products without a contract with carriers. These mutual necessities engender interesting strategic relationships and interactions among them. In a broader context, the ICT ecosystem contains companies from two additional segments: hardware component manufacturer and media companies.

1.2 Prior Work

Although each subsequent chapter contains focused literature review specific to the context of the study presented in the chapter, it is appropriate to review prior work in line with the motivation up front so as to provide a broad background and perspective for the whole dissertation. We first briefly review prior work in the research domains that we draw on and then review notable methodologies employed in this dissertation aside from the standard empirical methods.

1.2.1 Research Domains

This dissertation draws on the extant literature in five distinct but related research domains: enterprise transformation, interfirm alliances, new product development, platform strategy, and firm value of innovation.

Enterprise transformation proposed by Rouse (2005) argues that concerted changes in multiple layers of organizations must occur in order for a complex enterprise to be transformed in a desired direction. Enterprise transformation touches the issues such as how to design an organization (Hannan and Freeman, 1984) and what kind of leadership is necessary (Tichy and Devanna, 1986). Rouse (2005) proposes three dimensions to look after during transformation: means, ends, and scope. In other words, the manager in charge of enterprise transformation should keep in mind where to go, how to go, and which part of the organization to change. This task, however, is easier said than done. Basole et al. (2013b) lists the challenges and opportunities for enterprise transformation research. One of the challenges is that environment that an enterprise faces is dynamic, so having a successful enterprise transformation is like hitting the bull's eye on moving targets. Chapter 2 provides a visual description of the transformation path that the ICT ecosystem took over the past two decades, which helps managers better assess the as-is state and envision the to-be state of the enterprise. Chapter 6 aims to develop a more active measure to manage complexity in enterprise transformation by leveraging data-driven clustering and simulation methods.

What makes enterprise transformation research complex is that the interdependence among constituents of the business ecosystem. Because of the interdependence, one company's action brings about consequences, not only to itself, but to its rivals and collaborators (Oxley et al., 2009). Companies today hardly create value alone (Basole and Karla, 2012; Dhanarag and Parkhe, 2006). Rather, they form various types of formal and informal relationship with each other to achieve shared goals. Interfirm alliance represents a formal collaboration aspect between two or more companies. Depending on the shared goals, interfirm alliances can be categorized as exploratory such as R&D collaborations or exploitive such as licensing agreements (March, 1991; Rothaermel and Deeds, 2004). Research using the interfirm alliances data sheds light on understanding the issues of enterprise transformation. For example, Basole (2009) uses visualization of interfirm alliances to show enterprise transformation in the application developer network. The visual description of the ICT ecosystem transformation portrayed in Chapter 2 is also based on the interfirm alliances data. Chapter 6 additionally consider mergers and acquisitions (M&A) as a formal relationship between firms.

Developing a new product is one of the reasons why companies join forces in a formal collaboration (Kalaignanam et al., 2007). The NPD literature is of particular importance for this dissertation. The practice of NPD has been studied in multiple layers of abstraction. At the firm level, for instance, how to develop an optimal resource allocation scheme for NPD and how to select the right NPD projects over multiple screening stages are the main issues for managing the NPD process within a firm (Chao and Kavadias, 2008; Chao et al., 2009, 2014). At the product level, on the other hand, a firm engaging in NPD is often conceptualized as an agent in a high-dimensional space searching for an improved configuration of product/service components (Kauffman and Weinberger, 1989; Kauffman et al., 2000; Rivkin and Siggelkow, 2007; Billinger et al., 2014). The search space theory assumes that there is a hypothetical space of potential idea on product/service configuration and agents are looking for a better solution under feasible cost within the space. Agents cannot always move freely in the space because of the endogenous trade-offs between different technological aspects (Frenken and Nuvolari, 2004; Murmann and Frenken, 2006). Chapter 3 proposes a revised search space model constrained by external digital platforms. We model that companies explore the constrained search space by means of managing product family (Kekre and Srinivasan, 1990; Fisher and Ittner, 1999). Chapter 4 investigates how NPD is influenced by the choice of alliance partners.

Considering that platform choice constrains the search process for better products, choosing the right platform is important for manufacturers. Platform choice necessarily opens up a discussion on the two-sided market (Rochet and Tirole, 2003, 2006; Armstrong, 2006) because the platform in its classical meaning is to connect agents divided in two or more sides. For example, newspaper connects advertisers and readers and E-bay matches buyers and sellers. In the context of this dissertation, platform connects application developers and end users. There are many theoretical (Weyl, 2010) and empirical (Rysman, 2004) work on platform competition and strategy. While the importance of the platform is widely agreed, most studies focus on the implications for the companies that aim to build a successful platform. Our contribution to this literature lies in theorizing the role of platforms in the NPD process for manufacturers in Chapter 3.

It is almost axiomatic that developing an innovative product or service enhances the value of the company. The standard way to make a causal inference on whether certain events have an impact on the firm value reflected on stock market performance is event study methodology (Fama et al., 1969; MacKinlay, 1997). Using event study, several empirical studies indeed confirm that new product development and innovation have positive implications for firm value (Bayus et al., 2003; Fosfuri and Giarratana, 2008; Girotra et al., 2007; Sood and Tellis, 2009). While most studies use patenting activities as a proxy for innovation, there are a few studies that relate product-level technical specifications with firm value (Koski and Kretschmer, 2010). Using a multi-country event study model following Park (2004), Chapter 5 differentiates from and contributes to this literature by using an advanced measure for product innovativeness developed in Chapter 3 as a proxy of the product-level innovation.

1.2.2 Methods

In addition to standard regression analysis techniques such as ordinary least squares (OLS), logistic, and Poisson models, we employ five other methods that warrant some further explanation at least briefly up-front. We review key literature for each method we rely on in the main chapters.

The first method is network visualization. Growing significantly, this method has recently drawn much attention from research community studying complex network. Since Tufte and Graves-Morris (1983) lays out the theoretical foundation of the field, network visualization became an established method to show structural properties of a network. Venkatraman and Lee (2004), for example, uses network visualization to show how the game developer's choice of platform differs depending on platform's dominance and newness. Basole and Karla (2011) use a visualization approach to study structural changes in the mobile platform ecosystem. Basole et al. (2013a) proposes a way to combine visualization with analytics in the interfirm alliances context. Tools have advanced as well. About a decade ago, one of the most commonly used graph visualizing tools was Pajek (Batagelj and Mrvar, 1998). Pajek provides a simple yet powerful ways to interact with graph data and create a figure out of it. However, the size of graphs that research community is interested in has grown significantly and Pajek is not efficiently visualizing a large graph. Bastian et al. (2009) developed a new network visualization framework called Gephi. It aims to handle and visualize even a large graph effectively. Moreover, it allows users to download third-party plug-ins and layout algorithms for network visualization. Recent studies in various fields including data mining (Park and Lee, 2014) and public policy have used this new tool to communicate a large and complex network efficiently. Chapter 2 relies heavily on the network visualization methods to portray longitudinal enterprise transformation in the ICT ecosystem.

The second method is the difference-in-differences (DID) estimator. Suppose that we have two groups of observations: treated group and control group. In order to measure the average treatment effect, we are to compare these two groups. If our setting is a controlled experiment where other characteristics of the sample are drawn randomly, we just need to run statistical tests such as t-test that compare two groups of samples. However, as in many observational datasets, unobserved characteristics may be correlated with the treatment itself also as known as the selection bias. The DID method is intended to address the selection bias by not computing the post-treatment difference between the groups but comparing the differences between the groups across pre- and post-treatment periods. For instance, one of the first studies that used this method is Card and Krueger (1994). They exploited the event of minimum wage increase in New Jersey in 1992 to investigate whether the increase in the minimum wage leads to decrease in employment. They used Pennsylvania as a control group and found that minimum wage increase actually led to increase employment. In spite of some criticism that the power of this method is overrated (Bertrand et al., 2004), it is one of the most popular research methods in empirical studies (Abadie, 2005; Forman et al., 2008; Goldfarb and Tucker, 2011; Jung and Lee, 2014). Chapter 4 adopts this method to compare technical specifications of mobile handsets available on different network carriers before and after the iPhone.

The third method is an event study using stock market performance. Since Fama et al. (1969) proposed the standard event study method, it has been widely used by economics and management research (Binder, 1998). Although admitting the limitation that it is only possible for publicly traded firms, its strength is the ability to translate qualitative aspects of certain events into financial benefit or penalty to a firm. As non-U.S. firms have grown significantly, Park (2004) and Campbell et al. (2010) develop an extended version of event study that accommodates multi-country settings. Event study has been used for evaluating not only the financial implications of interfirm alliances (Oxley et al., 2009), but also the firm value impact of new product announcements (Hendricks and Singhal, 1997; Bayus et al., 2003). Kalaignanam et al. (2007) considers asymmetric product launching partnership using the event study. Their notion of asymmetry is mainly the size of allying firms—large or small. Chapter 5 focuses on different roles that companies take in an effort to create a new product. We look for potential asymmetric firm value implications for the different roles when a new product is launched. We also relate such abnormal returns with the technological superiority of the new products using a sophisticated measure of product innovativeness.

The fourth method is sequence clustering that estimates transition structure from sequences of events. The main objective of cluster analysis in general is to classify observations into a set of bins, so that researchers can generalize the observations. What a clustering algorithm does in essence is to maximize homogeneity within clusters and heterogeneity across clusters. Then, observations within the same cluster are similar to each other and those in different clusters are dissimilar as a result. Traditional clustering methods fall into two categories, agglomerative and divisive, depending on whether they search for clustering using bottom-up or top-down approach. A bottom-up approach starts with the same number of clusters to the number of observations. Each observation belongs to its own cluster at the beginning. Then, the algorithm starts merging clusters from those that are the most similar. Agglomerative hierarchical clustering is a representative example of this kind and k-means clustering can be viewed as this type (Rokach and Maimon, 2005). On the contrary, a top-down approach starts with a single clustering containing all observations and tries to find a cut that maximizes the difference between the two groups. Modularity clustering (Newman, 2006) and dependence clustering (Park and Lee, 2014) are examples of this type. In addition to these traditional clustering methods, nonparametric clustering methods have emerged recently for tasks such as clustering curves (Serban and Wasserman, 2005; Serban, 2008) or sequence of events (Hilton et al., 2015). The first half of Chapter 6 adopt Hilton et al. (2015) to identify clusters of firm behavior in forming alliances and M&A relationships with other firms.

Lastly, organizational simulation is the fifth method. Rouse and Boff (2005) provides a conceptual framework that covers from behavior modeling of individuals and groups to drawing insights and conclusions from the models. Simulation is especially useful when a random experiment is hardly feasible, researchers are interested in how structural property affects organizational outcome, or the problem does not yield a closed-form or analytical solution. As a classic example, March (1991) used artificial coding to show different types of organizational learning: exploration and exploitation. Arthur (1994) demonstrated emergent pattern of collective behavior using the El Farol problem as an example. Bodner and Rouse (2007) studied R&D process using organizational simulation and Park et al. (2012) studies healthcare delivery system using the multi-level organizational simulation to create a policy flight simulator. Organizational simulation could model things from individual behavior responding to incentives (Baumann and Stieglitz, 2014) to firm behavior as an agent searching for a better solution given the situation it is in. Harrison et al. (2007) surveyed papers that used simulation method in the management and organization literature. They argue the management and organization literature should embrace organizational simulation as an acceptable method more proactively. As a result, a growing number of research is now using organizational simulation to study individual firm's behavior in a competitive environment. The latter half of Chapter 6 uses organizational simulation informed by the clustering results to assess the impact of organizational learning on overall ecosystem network structure.

1.3 Research Objectives

In this section, we present the main research questions for Chapters 2 through 6 and aim to provide a consistent storyline that flows through the research theme of the dissertation as a whole.

The dissertation begins with Chapter 2 that tackles the problem of providing an effective bird-eyed view for the entire ecosystem of interest. Among many types of relationship between players in the ICT ecosystem, we chose the interfirm alliances network as a target context to start with. While firms can collaborate in many ways, the interfirm alliances capture explicit effort of value co-creating process in the ecosystem. Considering firms are operating in different industries (or segments), alliances can be broadly divided into two categories: within the segment and across the segment. Firms operating in the same industry are potentially competitors to each other, so alliances between such firms can be regarded cooperatively competing—coopetition. In contrast to coopetition, collaboration across industry represents blurring of industry boundaries—convergence. Lastly, from the network structure perspective, we are interested in whether the entropy of the whole ecosystem increases or decreases over time—complexity. Thus, the research questions for Chapter 2 can be summarized as follows.

Research Question 1 *How can the enterprise transformation path be quantified and efficiently described using the visual analytics tools? What are appropriate quantitative measures for ecosystem-level coopetition, convergence, and complexity?*

After looking at the network structural aspects of interfirm alliances, we zoom into the microscopic context of the mobile handset industry to look into the product innovation process. We start with developing a measure for the innovativeness of products. We particularly focus on smartphone as a target product context because digital platforms started playing an active role in smartphone after the basic or the feature phone era. The notion of innovativeness is fuzzy to define for a smartphone because people value technological aspects differently: one may like longer battery life and the other faster processing time. This fuzziness makes it a good context in which we can investigate how to quantitatively measure innovativeness in multi-dimensional technological space. Once we quantify innovativeness of smartphones, we compare them with respect to firm strategies in the search space constrained by digital platforms. Given that innovative product is an outcome of the search process in a search space, we view smartphone manufacturer sets search strategies in a certain multi-dimensional technological space bounded by the platform developer. The research questions for Chapter 3 are as follows.

Research Question 2 *How can we measure and compare innovativeness in multi-dimensional technological space? How are product family management and platform choice strategy associated with product innovativeness of the device manufacturer?*

After investigating the interaction between product innovativeness and digital platforms, we turn to the dyadic relationship between manufacturer and service provider. In the mobile handset industry, manufacturers sell products through service providers' subscriber network. Manufacturers compete with others in the same network. In this sense, service providers can play a gate-keeping role to manufacturers.

Leveraging this position, service providers may be able to intensify manufacturer-side competition by introducing a strong product in their network. We can also expect that the increased level of competition can sustain itself even after the impetus is removed. Moreover, this effect can influence another product category than the focal product category. Labeling these two spillover effects as temporal and horizontal, we formulate the research questions for Chapter 4 as follows.

Research Question 3 *Can service provider regulate the level of competition on the manufacturer side? Are there any temporal and horizontal spillover effects?*

In the end, we would like to know whether product innovation matters in dollar terms to the firm. One way to measure such firm value is event study measuring abnormal returns in stock market performance. We measure abnormal return of new product announcements for all three types of players involved in new smartphone development: hardware manufacturer, service provider, and platform developer of a given product. Do the launches of new products bring about positive abnormal returns? If so, do more innovative products lead to higher positive abnormal returns? Potentially, this effect may vary between the three types of firms. It is also possible that the market reacts differently across announcement and release of new products. These are the research questions for 5.

Research Question 4 *Is the launch of an innovative product recognized as a positive event for firm value by the stock market? What is the differential firm value of smartphone launch announcements for device manufacturers, service providers, and platform developers? Is there differential market reaction to announcement and release of products?*

The previous research questions mainly involve empirical investigations analyzing how the ICT ecosystem has transformed over past two decades, how innovation in new products interacts with interfirm relationship, and whether the innovation pays off. Our last research question concerns identifying inherent community structure and developing a simulation framework that helps formulate future research hypotheses. While Chapter 2 visualizes the competitive dynamics and strategic interaction based on predefined industry segments, the network structure possesses inherent clusters based on link formation structure. We then aim to build a tool that mimics the core mechanisms of ecosystem formation processes. The research questions for Chapter 6 are as follows.

Research Question 5 *Is there an inherent community structure inferred from the ICT ecosystem network structure? How can a simulation framework replicate the ICT ecosystem structure that allows systematic generation and test of potential hypotheses in complex enterprise systems?*

1.4 Outline

This dissertation is a culmination of the research effort to address the research questions presented in the previous section. The questions encompass analyzing innovation management process in a complex business ecosystem and developing a framework for decision support systems utilizing various computational techniques. The following five main chapters present detailed research with varying scopes, methodologies, and domains. Figure 2 outlines the overall structure of the dissertation.

Chapter 2 proposes a way to visualize complex enterprise systems as a network and to present a persuasive story on the transformation path by leveraging the power of visualization technique. This chapter consists of a research paper. Basole et al. (2015b), published in *Telecommunications Policy* and titled "Coopetition and Convergence in the ICT Ecosystem," analyzes enterprise transformation that has occurred in the ICT ecosystem over the past two decades using interfirm alliances data. This study focuses on quantifying and visualizing the competitive dynamics shaping the ICT ecosystem, grounded in theories of complex systems, strategy dynamics, and

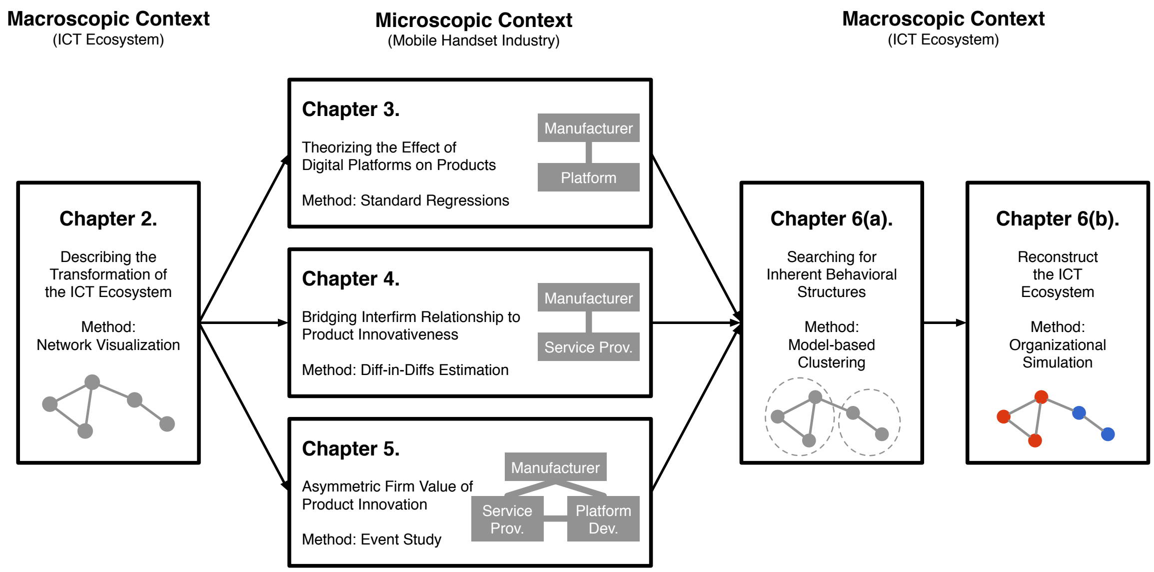


Figure 2: Dissertation Outline

industry life cycle. It defines and develops graph and information theoretic measures of coopetition, convergence, complexity, and velocity of the ICT ecosystem. Then, it frames "transformation path" of the ICT ecosystem and maps the trajectory using complex network visualizations. The transformational path of the industrial ecosystem is decomposed into two dimensions: coopetition and convergence. The ICT ecosystem portrayed in the chapter consists of five industry segments defined by 58 standard industry classification (SIC) codes ranging from hardware device manufacturer to software developer and media advertisers. As interfirm alliances exist within and across different segments, we focus on dissecting alliances into two types: within-segment and cross-segment alliances. Assuming firms in the same industry segment are competitors, within-segment alliances denote cooperative competition—coopetition. On the other hand, we interpret alliances across segments as blurred industry boundaries and convergence of the ecosystem. This chapter extends Basole (2009) and Basole and Karla (2011) by applying network visualization to the ICT ecosystem. It also quantifies and illustrates the insights by Basole and Rouse (2008) in which they conceptualize the complexity of the ICT ecosystem.

From Chapter 3, we dive into the more detailed context of the mobile handset industry embedded in the broader ICT ecosystem. We start with theorizing a revised search space model in the presence of digital platforms. This chapter then provides empirical evidences about how a device manufacturer strives for product innovation in the search space constrained by digital platforms. This chapter particularly delves into the smartphone industry as digital platforms do not play a major role in basic and feature phone categories. To theorize a revised search space model, we draw on the classic search space theory and dominant designs Utterback and Suárez (1993); Suárez and Utterback (1995). Among many possible aspects of firm strategy on innovation, we focus on the search strategy and its interaction with search boundaries imposed by digital platforms. As a search strategy, we look at how manufacturer extends product family in a constrained search space. As digital platforms externally impose search boundaries that manufacturers are bound, the manufacturer's choice in platform mix is another dimension of firm strategy in this chapter. This study is based on the technological evolution of smartphones including physical characteristics, computing performance characteristics, and features over the past decade. We propose an index to measure innovativeness of a smartphone upon which we test the four main hypotheses. Regarding product family management, we find that the number of product families and more experience in a certain family are positively associated with product innovativeness. For platform strategy, choosing exclusively a newer platform is positively associated with product innovativeness. Combining the product family management literature with platform strategy from the perspective of product innovation, this chapter contributes to the understanding of how operational management and platform strategy affect product-level innovativeness in the smartphone industry.

Chapter 4 turns to the relationship between manufacturer and service provider, while the previous chapter looks at the relationship between manufacturer and platform developer. In particular, we exploit an industry-wide transformative event: the exclusive launch of the iPhone on the AT&T's service network. Leveraging this setting, we investigate how exclusive contract of a service provider can be leveraged to induce supply-side competition on product innovation, which leads to virtuous self-sustaining cycle. This chapter uses difference-in-differences estimation method to estimate the impact of the iPhone on the competitive landscape. Over the exclusive contract period between Apple and AT&T, other competing device manufacturers supplied their technologically superior phones to AT&T. We find this competition-induced product enhancement effect survived even after the exclusive contract had expired. These findings are supported by various robustness checks including estimation using narrow time window and testing against placebo events. We also find some evidences that manufacturers enhance their products for AT&T in the technical aspects that the iPhone excelled, which suggests manufacturers attempt to keep up with the new technological expectation disrupted by the iPhone. Lastly, we contrast heterogeneous responses from different major manufacturers including Samsung, LG, Motorola, and Nokia. This chapter shows how exclusive acquisition of a superior product can create a virtuous cycle of inducing superior products from other competing suppliers through product innovation contest on service network.

Chapter 5 examines potentially asymmetric impact of product innovation on the market value of manufacturer, service provider, and platform developer in the mobile handset industry. We also compare the market impact of announcement and release of new products to identify temporal asymmetry in market reaction to product innovation. We use multi-market event study model involving three factors: local market index, global market index, and trade-weighted exchange rate change. Using this model, we measure the magnitude of abnormal returns of individual stock price of the related firms listed in different markets around the world. We confirm positive abnormal returns to manufacturer firm value. Exploiting the temporal gap between announcement and release, we find that a product announcement leads to positive cumulative abnormal returns to the manufacturer, while the actual product release is associated with negative firm value. The magnitude of negative change upon release is smaller than that of positive impact upon announcement. Thus, we observe net positive impact of a new product launch throughout announcement and release and we interpret these results as an evidence of fluctuating market expectation uncertainty on a product. Moreover, we find that the more innovative a new product is, the more positively market reacts. This chapter contributes to the extant combined literature on new product development and event study by taking into account the influence of detailed product technical specifications. Most previous work in the area uses patent as innovation outcome (Trajtenberg, 1990; Sherry and Teece, 2004) largely disregarding detailed product characteristics. As patent is not a consumable or usable product to end consumers, there is a conceptual gap between the commonsense innovation and the patenting behavior. Although a few papers look at the technical specifications (Koski and Kretschmer, 2010), they look at only one or two technical aspects to stand as a proxy for the level of product superiority. This chapter considers a number of technical specifications altogether to provide a holistic view on product innovation.

Chapter 6 steps back to zoom out to view the entire ICT ecosystem again. While Chapter 2 focuses on describing and visualizing the ecosystem transformation based on the predefined industry classification scheme, this chapter aims attention to make inferences based on firm behavior. Using a model-based clustering algorithm developed by Hilton et al. (2015), we estimate transition matrix and inter-arrival time matrix that describe how firms form a sequence of relationships of various types. Clustering based on these estimation results, we identify five clusters of firms exhibiting different behavior. Each of the five clusters informed by the algorithm contains a mix of companies from different industry segments, so our clustering results provide additional information on the ecosystem structure on top of the established predefined industry classification. Based on the clustering results, we build a simulation model that replicates the ICT ecosystem and incorporates organizational learning model. Firms in the simulation framework copy the behavior of prominent benchmarks in the network, which influence the overall network characteristics of the ecosystem.

Chapter 7 finally summarizes the findings from the five main chapters and discusses implications for research and practice in technological innovation management in the business ecosystem. The dissertation concludes with directions for future work. We provide a few preliminary ideas for future work extending this dissertation based on a mix-and-match among methods and domains used in different chapters.

CHAPTER II

VISUALIZING AND DETECTING THE PATH OF BUSINESS ECOSYSTEM TRANSFORMATION

2.1 Introduction

It is well known that the information and communications technology (ICT) ecosystem has experienced a significant transformation over the past two decades (Christensen and Anthony, 2004; Fransman, 2010). Driven by rapid technological advances, changing societal preferences, and shifting economic and regulatory conditions, firms had to continuously seek ways to improve existing and create and deliver new value propositions in order to grow and survive (Iansiti and Richards, 2006). These complex dynamics continue to persist and have led the ICT ecosystem to become one of the most dynamic and fiercely competitive business environments.

While the evolution of the ICT ecosystem has been an important line of inquiry for scholars (Moore, 1993; Malerba et al., 1999; Agarwal and Bayus, 2004), some issues remain unanswered. Particularly limited work has been done in quantifying and visualizing the competitive dynamics shaping the ICT ecosystem. Rather than using perceptual measures, a quantitative visual approach provides a more objective foundation critical for managerial sense and decision making. Moreover, it also enables a comparative analysis of patterns within and across industries as well as a way to answer foundational business ecosystem strategy and policy questions.

We concentrate our study on two competitive dynamics: coopetition and convergence. Coopetition refers to the cooperation between competing firms leading to possible win-win conditions. Convergence refers to the blurring of industry boundaries. Both of these dynamics have been shown to be prevalent in the ICT ecosystem, as firms are continuously searching for new ways of creating and delivering value (Basole and Rouse, 2008).

The ICT ecosystem is a particularly suitable domain to study coopetition and convergence as it is highly dynamic and brings together a variety of different market segments globally (Basole, 2009). At the same time, the role and power of existing players is challenged by continuously emerging new players, creating an interesting dynamic and tension of who will ultimately emerge as leaders. Previous studies have analyzed the nature and dynamics of interfirm relationships (Basole, 2009; Rosenkopf and Padula, 2008; Basole and Karla, 2012), investigated the role of platforms (Basole and Karla, 2011), and evaluated different business models and strategies (Li et al., 2002; Bouwman et al., 2008; Peppard and Rylander, 2006).

We build on this prior work and quantify and visualize the coopetition and convergence shaping the ICT ecosystem. We ground our inquiry of ecosystem coopetition and convergence in theories of complex systems, strategy dynamics, and industry life cycle. Using a unique longitudinal dataset, we define and develop graph and information theoretic measures of coopetition, convergence, complexity, and velocity of the ICT ecosystem. We frame the "transformation path" of the ICT ecosystem using these novel metrics and map the trajectory using advanced visualization approaches. In doing so, we address the call of developing new ecosystem metrics, identifying competitive characteristics shaping the ICT ecosystem, and visualizing the expanding ICT ecosystem.

The remainder of the chapter is organized as follows. Section 2.2 reviews the theoretical foundations. Section 2.3 presents our data and methodology. Analysis and visualization of results are presented and discussed in Section 2.4. Section 2.5 concludes with a discussion of implications and future research opportunities.

2.2 Theoretical Foundation

Our study draws on four interrelated literature streams: ecosystems as complex systems, coopetition, convergence, and industry life cycle.

2.2.1 Ecosystems as Complex Systems

The conceptualization of industries and markets as business ecosystems has been gaining traction in the management, strategy, and policy literature (Iansiti and Richards, 2006; Moore, 1996). The ecosystem perspective, adapted from the biological and ecological sciences, is based on the premise that industries consist of a heterogeneous and continuously evolving set of constituents that co-create value and are codependent for survival (Iansiti and Levien, 2004).

The complex systems lens posits that constituents are interconnected through a complex, global network of relationships (Basole and Rouse, 2008), allowing them to share risks, have access to synergistic knowledge, and be responsive to changes in the institutional environment (Eisenhardt and Schoonhoven, 1996; Basole and Karla, 2011; Russell et al., 2011). Scholars have shown that these interfirm networks are a particularly effective organizational form to improve firm performance, speed of innovation, and organizational learning (Ahuja, 2000; Zaheer et al., 2000). Ecosystem players come from a variety of market segments and fill particular roles such as keystones, dominators, and niche (Iansiti and Levien, 2004; Basole, 2009). As it is quite unlikely for a single market segment to deliver all products or services to end-consumers, successful value creation and delivery requires a careful orchestration between firms across these segments (Basole and Karla, 2012; Dhanarag and Parkhe, 2006).

Furthermore, research has shown that ecosystems are shaped and driven by a broader societal, technological, economic and regulatory context (Basole and Rouse, 2008). This argument is rooted in the idea of "embeddedness" presented in Granovetter's seminal article on economic activities (Granovetter, 1985). Specifically, it states that economic activities cannot be viewed in isolation from other institutions or from the technological, political, and social context in which firms exist. The initiatives in the Telecommunications Act of 1996, for instance, fundamentally transformed the structure of the ICT industry. The launch of the iPhone in 2007 triggered enormous new activities in the technology industry (Basole and Karla, 2012). Much more subtle are people's social and cultural norms and expectations where, over time, changes enable new businesses and approaches to business. The extent and level of service expectations have undoubtedly been influenced by the immediacy of instantaneous and constant connectivity (Basole and Rouse, 2008). These vignettes illustrate that these contextual influences can have a deep impact on economic activities and must therefore be considered when conceptualizing the structure and dynamics of business ecosystems.

The evolving complexity of ecosystems presents both challenges and opportunities (Basole and Rouse, 2008). As ecosystems become increasingly complex, firms must be capable of identifying and appropriately managing this complexity in order to remain competitive and survive. On the other hand, ecosystem complexity can expand the opportunity space enabling firms to create new value propositions. Successful firms find ways to navigate this complexity by monitoring their relative position in the ecosystem and identifying opportunities they are exposed to. Understanding and managing ecosystem complexity is also an important task for policymakers as it enables them to formulate effective systemic policies and avoid unintended and potentially negative consequences.

This study builds on this existing work and applies a complex networked systems lens to identify, quantitatively assess, and visualize the evolution of two orthogonal forces shaping the mobile ecosystem: coopetition and convergence.

2.2.2 Coopetition

Business is both war and peace. In today's dynamic business environment, firms have to compete and cooperate at the same time in order to grow and survive. Brandenburger and Nalebuff (1996) refer to this phenomenon as cooperative competition, or coopetition. The cooperative aspect of coopetition refers to the collective use of shared resources to pursue common interests; the competitive aspect refers to the use of shared resources to make private gains in an attempt to outperform partners (Khanna et al., 1998; Tsai, 2002).

Coopetitive relationships are considered complex as they consist of actors that produce and market the same products (Bengtsson and Kock, 2000). Coopetition replaces the traditional neoclassical view of competition. Early research has argued that that collaboration among rivals may inhibit competition by facilitating collusion or by shaping industry structure in anticompetitive ways (Porter and Fuller, 1986). More recently, however, scholars have shown that firms engaged in coopetition can generate significant economic rents and achieve superior long-run performance (Lado et al., 1997; Gnyawali and He, 2006; Gnyawali and Park, 2011). Hamel et al. (1989) argued that coopetition through alliances is not devious, but in fact reflects a commitment and capacity for each partner to absorb the skills of the other (Hamel et al., 1989), leading to "coopetitive advantage" (Dagnino and Padula, 2002).

Coopetition is particularly valuable in industries characterized by short product cycles, strong technological convergence, and high R&D costs (Gnyawali and Park, 2009; Pellegrin-Boucher et al., 2013). It is therefore quite pervasive in the ICT industry in general (Ritala et al., 2008; Ancarani and Costabile, 2010) and the mobile ecosystem in particular (Maitland et al., 2002; Peppard and Rylander, 2006; Basole, 2009; Gueguen, 2009; Gueguen and Isckia, 2011; Zhang and Zhu, 2011). Coopetition enables firms to access complementary resources from external partners, while at the same time requiring them to continuously improve their activities and market offers in order to maintain and develop their competitive advantage (Bengtsson and Kock, 1999, 2000; Gnyawali and He, 2006; Lado et al., 1997). Alliances among competitors has also been shown to provide an opportunity for imposing technological standards and allow firms to become market pioneers by creating "lock-in" capabilities (Shapiro and Varian, 1999; Gueguen, 2009). Furthermore, coopetition accelerates R&D efforts, significantly reduces costs, diversifies the portfolio of products or services, and drives higher levels of consumer satisfaction (Dittrich and Duysters, 2007; Gueguen, 2009; Ritala and Hurmelinna-Laukkanen, 2009; Pellegrin-Boucher et al., 2013).

Coopetitive relationships, however, can also have negative and unintended effects, including the increased risk of opportunistic behavior (Brandenburger and Nalebuff, 1996), threat of knowledge expropriation (Hamel, 1991; Oxley and Sampson, 2004), erosion of trust (Nieto and Santamaría, 2007), and disruption of existing business models (Bonel and Rocco, 2007). Before entering coopetitive relationships, firms must take these downsides into account and judiciously evaluate potential partners.

This study follows the definition of coopetition by Bengtsson and Kock (1999)—i.e. collaborating with direct competitors (Bengtsson and Kock, 2000)—and develops a network analytic measure to understand the level of coopetition in the ICT ecosystem. Figure 3 conceptualizes our measure for coopetition.

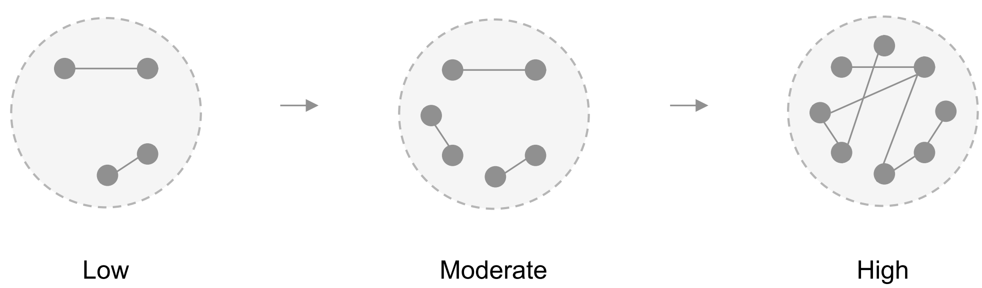


Figure 3: Levels of Coopetition

2.2.3 Convergence

Convergence refers to a transformation process that blurs boundaries by unifying value propositions, technologies, or markets (Greenstein and Khanna, 1997). Scholars have identified several types of convergence, including knowledge, technology, and industry (Hacklin, 2008).

Knowledge convergence is the combination of knowledge bases and the erosion of boundaries that define and isolate industry-specific knowledge (Hacklin et al., 2009). It is sometimes also referred to as scientific convergence, a process where distinct scientific disciplines begin to cite each other and collaborate (Curran et al., 2010). Knowledge convergence is generally motivated by an industry actor's identification of new opportunities lying at the edge of its industry border and awareness of the potential of combining own knowledge with external one, thereby leading to novel and potentially innovative activities.

Technological convergence is closely linked to knowledge convergence and is defined as the combination of previously distinct technologies into a common product (Gambardella and Torrisi, 1998). Technological convergence leads to new value-creating opportunities and product and service offerings (Stieglitz, 2003). There are many examples of technological convergence in the ICT industry, including the bundling of a mobile phone and digital camera into a camera phone or a game console and media player into a portable entertainment solution (Han et al., 2009).

When technologies converge and applications from distinct domains are combined, they infringe on existing value-creating territories of underlying sectors and industries (Hacklin et al., 2009). This leads to collision of business models and gradual blurring, or redefinition, of market boundaries (Porter, 1985; Hamel and Prahalad, 1994). This phenomenon is called industry convergence (Hacklin, 2008). Prior research has shown that industry convergence often leads to a new cross-industry segment that widens markets, lowers barriers to entry and increases competition (Borés et al., 2003). Moreover, industry convergence can lead to reconfiguration of the value chain through the addition or elimination of activities (Greenstein and Khanna, 1997; Wirtz, 2001), consolidation through mergers and acquisitions (Chan-Olmsted, 1998; Lee and Colarelli O'Connor, 2003), as well as a complete shakeout of players from the ecosystem (Steinbock, 2003; Basole, 2009).

Industry convergence is particularly prevalent in the ICT context (Katz, 1996; Duysters and Hagedoorn, 1998; Chan-Olmsted, 1998; Gambardella and Torrisi, 1998; Wirtz, 2001; Liu, 2013). Traditionally separate market segments, such as broadband, cable, and telephony for instance, are now deeply intertwined, providing integrated, bundled digital products and services to consumers (Basole and Rouse, 2008). Scholars have attempted to measure industry convergence in many ways, including corporate diversification (Teece et al., 1994; Gambardella and Torrisi, 1998; Fan and Lang, 2000), knowledge/technology relatedness (Breschi et al., 2003; Joo and Kim, 2010; Makri et al., 2010), patent collaboration (Fai and Von Tunzelmann, 2001; Curran et al., 2010; Curran and Leker, 2011), and macroeconomic input-output analysis (Xing et al., 2011).

Our study builds on this work and develops a network analytic measure of industry convergence. Figure 4 conceptualizes our measure for convergence.

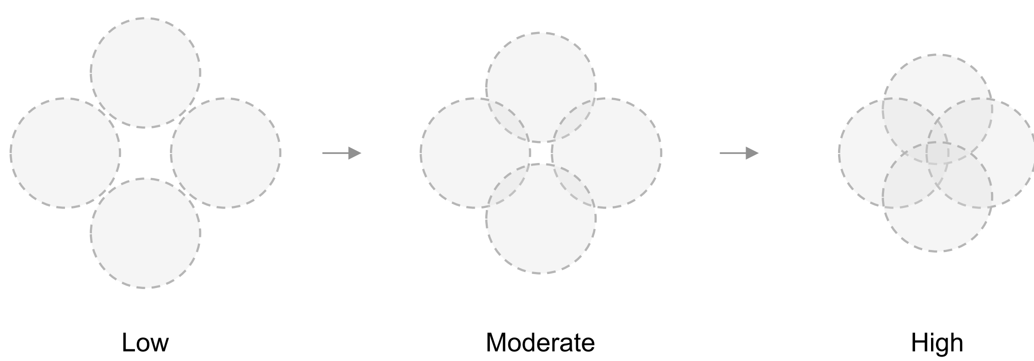


Figure 4: Levels of Convergence

2.2.4 Industry Life Cycle

The level and extent of coopetition and convergence must be considered in the context of ecosystem maturity. Originally presented by Utterback and Abernathy (1975), the theory of industry life cycle presents a formidable perspective to contemplate ecosystem coopetition and convergence. The industry life cycle theory argues that firms compete based on alternative "product designs" in early industry stages. Firm entry is rampant and there is widespread experimentation with alternate designs (Argyres and Bigelow, 2007). Over time, product innovation decreases while process innovation increases, leading to the emergence of a "dominant design" (Christensen et al., 1998). During this phase firms compete on cost rather than design and economies of scale lead to industry consolidation, forcing out smaller firms (through exit or acquisition) and raising entry barriers (Argyres and Bigelow, 2007). Similarly, Klepper and colleagues (Klepper and Graddy, 1990; Klepper, 1996, 2002) showed that all industries evolve through prototypical phases of a life cycle and undergo transformations in structure, diversity, and dynamics.

The industry life cycle lens has been used extensively in the study of ICT industry. Mazzucato (2002), for example, examined the maturation of the PC industry. Kwak et al. (2012) investigated the evolution of alliance structure in standard setting in the telecommunications industry. Rice and Galvin (2006) studied the evolution of alliance patterns over industry life cycle for multinational electronics firm. Filson (2001) examined the life cycle impact on price, quantity, quality of products within the ICT industry.

Agarwal and Sarkar (2002) argued that three theoretical lenses have been predominantly used to explain industry life cycles. Evolutionary economists, for instance, have shown that industries grow slowly at first, then expand rapidly until the number of firms reaches a peak. The process reverses thereafter, despite continued industry growth, until a few large firms come to dominate the market. This pattern has been observed across many different industries. From a technology management perspective, the life cycle of an industry is driven by technological discontinuities (Anderson and Tushman, 1990). This perspective suggests that an industry evolves through long periods of incremental change punctuated by times when radical, new, superior technologies displace old, inferior ones (Tushman and Anderson, 1986; Agarwal and Sarkar, 2002). Organizational ecologists argue that dynamic models of legitimacy, resource attraction, and competition explain the founding, growth, and decline of industries (Hannan and Carroll, 1992).

Together, these complementary perspectives emphasize the fact that firms face different competitive environments at different phases and thereby different levels of survival risk (Agarwal and Sarkar, 2002). The level and extent of convergence and coopetition can thus vary based which particular industry life cycle phase the ecosystem is in. Our study leverages the industry life cycle lens to explain the position and trajectory of the ICT ecosystem in the coopetition-convergence opportunity space (shown in Figure 5).

2.3 Data and Methods

2.3.1 Data

The primary dataset used for this study is Thomson Reuters SDC Platinum[1], a well-established, comprehensive, and accurate commercial database commonly used in the study of global interfirm relationships across multiple sectors (Schilling, 2009). It has been used extensively in strategic management, finance, research policy, and the management and organization sciences (Hsu, 2006; Sampson, 2004; Schilling and Phelps, 2007). SDC Platinum contains detailed information on joint ventures and alliances (i.e. R&D, sales and marketing, supply and manufacturing, licensing and distribution), curated from the U.S. Securities and Exchange Commission (SEC) filings, trade

[1] http://thomsonreuters.com/sdc-platinum/

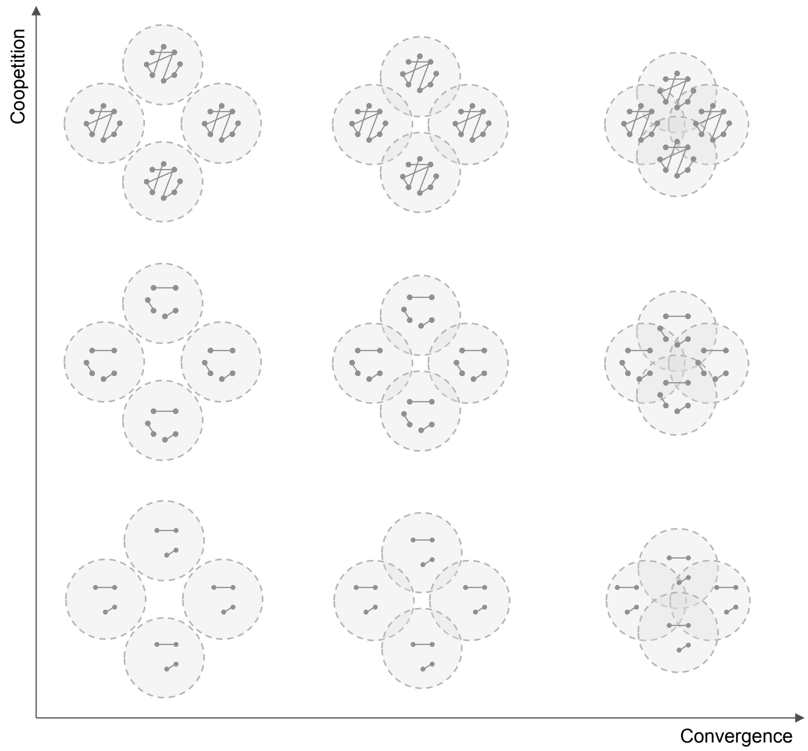


Figure 5: Convergence-Coopetition Landscape

publications, wires and news sources. The primary strength of this database is its global and cross-industry scope (Schilling, 2009). It covers at least one alliance of each of the 1,000+ four-digit Standard Industrial Classification (SIC) codes. In addition, it provides searchable access to 200+ additional data elements, including names, SIC codes and nationality of firm participants, and relationship types, terms and synopsis.

Given the growing scope of the ICT ecosystem, it is important to specify the boundaries of the system being studied (Basole and Karla, 2012). To meet our goal of mapping the evolution of coopetition and convergence, our boundary criteria had to be as inclusive as possible. We consequently used all four-digit SIC codes that make up both incumbent and emerging parts of the ICT ecosystem (Basole, 2009; Wulf, 2012). This resulted in an identification of 58 four-digit SIC codes (shown in Table 1). It is important to note that each four-digit SIC code represents one ecosystem segment in our study.

Table 1: Industry Segment Classification (adapted from Basole (2009) and Wulf (2012); nec stands for "not elsewhere classified".)

Sector	SIC Codes	SIC Code Description	Color Code
Hardware Components	3671	Electron tubes	Blue
	3672	Printed circuit boards	
	3674	Semiconductors and related devices	
	3675	Electronic capacitors	
	3676	Electronic resistors	
	3677	Electronic coils, transformers, & other inductors	
	3678	Electronic connectors	
	3679	Electronic components, nec	
	3691	Storage batteries	
	3692	Primary batteries, dry and wet	
	3694	Electrical equipment for internal combustion engines	
	3695	Magnetic and optical recording media	
	3699	Electrical machinery, equipment, and supplies, nec	
	3827	Optical instruments and lenses	
	3861	Photographic equipment and supplies	
Hardware Equipment	3571	Electronic computers	Red
	3572	Computer storage devices	
	3575	Computer terminals	
	3577	Computer peripheral equipment, nec	
	3578	Calculating and accounting machines, except electronic computers	
	3579	Office machines, nec	
	3651	Household audio and video equipment	
	3652	Phonograph records and prerecorded audio tapes and disks	
	3661	Telephone & telegraph apparatus	
	3663	Radio & TV broadcasting & communications equipment	
	3669	Communications equipment, nec	
	3944	Games, toys, children's vehicles,exc. dolls, bikes	
Software	5734	Computer and computer software stores	Orange
	7371	Computer programming services	
	7372	Prepackaged software	
	7373	Computer integrated systems design	
	7374	Data processing services	
	7375	Information retrieval services	
	7376	Computer facilities management services	
	7377	Computer rental and leasing	
	7378	Computer maintenance and repair	
	7379	Computer related services, nec	
	7382	Security systems services	
Telecommunications	4812	Radiotelephone communications	Green
	4813	Telephone communications, except radiotelephone	
	4822	Telegraph and other message communications	
	4899	Communications services, nec	
Media	2711	Newspapers: publishing, or publishing & printing	Purple
	2721	Periodicals: publishing, or publishing & printing	
	2731	Books: publishing, or publishing & printing	
	2741	Miscellaneous publishing	
	4832	Radio broadcasting stations	
	4833	Television broadcasting stations	
	4841	Cable and other pay television services	
	7311	Advertising agencies	
	7312	Outdoor advertising services	
	7313	Radio, television, and publishers' advertising representatives	
	7319	Advertising, nec	
	7812	Motion picture and video tape production	
	7819	Services allied to motion picture production	
	7822	Motion picture and video tape distribution	
	7829	Services allied to motion picture distribution	
	8742	Management consulting services	

We then extracted all alliances between 1990 and 2012, in which at least one firm had one of the aforementioned SIC codes as its primary SIC code. To identify the date of alliance formation, we used the "Date Announced" field in SDC Platinum. Other dates, such as terminated or expired, are rarely reported. This led to an initial list of 62,910 unique firms (based on the six-digit Committee on Uniform Security Identification Procedures (CUSIP) identifier) and 66,192 alliances. Next, we limited our dataset to alliances that were completed/signed, extended, terminated, or expired; we thus excluded alliances that were on letter of intent, pending, or rumored. SDC Platinum also provides SIC codes for alliances. We thus also excluded alliances whose primary SIC code was not in our SIC list (i.e. some firms may form alliances in an entirely different industry). This led to a final dataset of 20,232 firms and 20,870 alliances (3,850 joint ventures (18.4%); 7,005 R&D and marketing (33.6%); 3,944 technology transfer (18.9%); 2,819 manufacturing, original equipment manufacturer (OEM), and supply chain (13.5%) ; 2,715 licensing (13.0%)).

Table 2 provides a summary of the geographic distribution of firms and alliances in our dataset. We used the taxonomy suggested by Curwen and Whalley (2013) to differentiate between major geographic regions.

Next, we constructed a firm-level ecosystem network using a weighted adjacency matrix. An adjacency matrix is a square matrix with nodes (e.g. firms) as both rows and columns. The presence of an alliance between firms i and j, denoted by x_{ij}, is coded as 1, and 0 otherwise. Given that alliances may contain more than two firms, we constructed relationship edges between all firms in an alliance. An alliance with three firms, for example, therefore would generate three edges. If a firm's primary SIC code was not our list, we dropped that firm from analysis. As this may result in an alliance with only a single valid firm, we dropped that alliance from further analysis as well.

Table 2: Geographic Distribution by Region

Region	Number of Firms -1997	-2002	-2007	-2012	Number of Alliances -1997	-2002	-2007	-2012
Western Europe	1,174	2,240	2,918	3,241	780	1,366	1,565	1,680
Eastern Europe	125	154	169	186	39	47	48	51
Middle East	76	127	187	217	11	16	26	31
Asia-Pacific	1,324	2,890	3,481	3,841	1,546	3,128	3,426	3,615
North America	4,390	7,781	11,344	12,342	7,079	10,425	13,062	13,771
Latin America	84	195	265	291	26	49	59	65
Africa	28	44	82	97	3	6	13	15
Cross-Region					4,038	6,292	7,611	8,232
Total	7,201	13,431	18,446	20,215	13,522	21,329	25,810	27,460

Entries in the matrix were scaled following the weighting scheme proposed by Zaheer et al. (2010), who argued that the strength of interfirm relationship is determined by the amount of knowledge exchanged. Consequently, R&D and marketing (5) were assigned the largest weight followed by technology transfer (4), supply chain, manufacturing, and OEM (3), and (exclusive) licensing (2). All other remaining alliance types were given a unit weight (1). For joint ventures, we looked into the alliance text of each agreement as suggested by Zaheer et al. (2010). If a joint venture was associated with another alliance type (e.g. R&D), we coded it as that type. If no alliance type was identified, based on author consensus, we assigned it to the lowest unit weight. If an alliance consisted of multiple types (e.g. marketing and manufacturing), we selected the maximum value of relevant alliance type weights. We did not consider relational direction, resulting in an undirected multiplex graph.

Similarly, we also constructed a segment-level ecosystem network using a weighted adjacency approach. Edges between two segments were weighted by the number and type of relationships between two firms between two segments. Each entry in the adjacency matrix was weighted to account for multiplexity and relationship type.

2.3.2 Measures

2.3.2.1 Coopetition

We considered several different network measures for coopetition. First, we considered segment network density (existing over all possible links) as a measure of coopetition. However as not all edges are equally likely to occur, we believed that density would penalize us for sparse segment networks and underestimate coopetition. Next, we considered weighted edge count between firms within a SIC as a measure of coopetition. However, this measure, even if normalized by segment size, would have favored larger segments. As a result, we decided to measure ecosystem coopetition using the number of connected components. A connected component is defined as a subgraph whose nodes are connected to each other by paths and not connected to other nodes in the supergraph. It thus measures the number of "pockets" of coopetition in the ecosystem. It is invariant to the variation of weighting schemes because it is a structural property of the whole network. As we are interested of coopetition at the ecosystem level we considered the total count and not an average or median across segments. Coopetition (Cp) is thus measured as:

$$Cp = |\,\text{set of connected components of } G\,| \tag{1}$$

where G is the firm-level network containing only the within-segment edges excluding cross-segment ones.

2.3.2.2 Convergence

Similar to coopetition, we also considered several different networks measure for convergence. We eliminated weighted network density as a measure as not all segment are candidates for interconnection and we would underestimate convergence. Thus, we decided to measure ecosystem convergence using the inverse transformation of the average path length of the inter-segment network. Since the current weighting scheme between segments represents "strength" of alliances between the two segments, we need to convert edge weight to represent "distance" between segments. We employed Gaussian radial basis function as our transformation to convert strength to distance.

$$\text{distance} = \exp(-\sigma \cdot \text{strength}) \tag{2}$$

We choose the attenuation factor σ to be 0.1 to ensure reasonable scale. Average shortest path length in the segment-level network, whose edges are weighted by distance according to Equation (2), measures the distances between all two pairs of nodes and then computes the average. The smaller the average shortest path length, the closer segments are to each other. Using the inverse relationship allows us to invert the average shortest path length to a measure of convergence; a network with low average shortest path length is consequently highly converged. Convergence (Cv) is thus measured as:

$$Cv = -\frac{1}{\sigma} \ln \sum_{s,t \in V} \frac{d(s,t)}{n(n-1)} \tag{3}$$

where V is the set of all segments, $d(s,t)$ is the shortest path length between segments s and t, and n is the size of V.

2.3.2.3 Complexity

We measure the complexity of the ecosystem using an information-theoretic entropy approach (Shannon, 1948; Basole and Rouse, 2008). Complexity measures the structural randomness of the firm-level network containing all unweighted within-segment and cross-segment edges. Based on the classical entropy formula, complexity (Cx) is measured as:

$$Cx = -\sum_{v \in V} \frac{\deg(v)}{n-1} \ln \frac{\deg(v)}{n-1} \tag{4}$$

where V is set of all firms, $deg(v)$ is degree of firm v, and n is the number of all firms in V.

2.3.2.4 Velocity

We measure the velocity of the ecosystem in terms of the two strategy measures, Cp and Cv. Velocity is a measure of the first derivative how an ecosystem changes. Velocity is thus computed as:

$$v_{Cp} = Cp(t) - Cp(t-1) \tag{5}$$

$$v_{Cv} = Cv(t) - Cv(t-1) \tag{6}$$

where v_{Cp} and v_{Cv} denote velocity along coopetition and convergence, respectively, and t is year.

2.3.3 Ecosystem Visualization

We used Gephi 0.82 beta, a leading open-source visualization platform, to portray the networks (Bastian et al., 2009) and computed network metrics using NetworkX (Hagberg et al., 2008).

To position segments in the network visualizations, we first used the neato layout algorithm (North, 2004) provided by GraphViz (Ellson et al., 2002). Noverlap layout included in Gephi was used where appropriate to avoid overlap between segment nodes. Once the positions of segment-level nodes were determined, its position is fixed throughout all graphics so that readers are not burdened to follow segments of interest across different time points. For firm-level network illustrating coopetition, we constructed network only by within-segment edges excluding cross-segment edges. We used random layout over a circular disk whose radius is proportional to the number of firms of each segment. The location of disks anchors on the location of segments determined by the segment-level network visualization. We used Matplotlib (Hunter, 2007) to create the evolutionary complexity heat map and maximum coopetition pocket size bar chart shown in Figures 7 and 10 respectively.

For clarity, readability, and aesthetic reasons, we also chose to group and visually encode our 58 ecosystem segments (as defined by the four-digit SIC code) using the five-sector approach proposed by Wulf (2012). The last column in Table 1 shows the color code we used for each segment. Each of these colors is used consistently throughout all visualizations.

2.4 Analysis & Discussion of Results

Figure 6 shows the cumulative growth of firms and relationships and the average number of relationships per firm from 1990-2012. The evolution indicates that, while the number of firms engaging in alliances is growing, the rate of alliance formation is decreasing. The average degree per firm reached a peak in the late 1990s (3.7) and has been decreasing moderately until now (2.6).

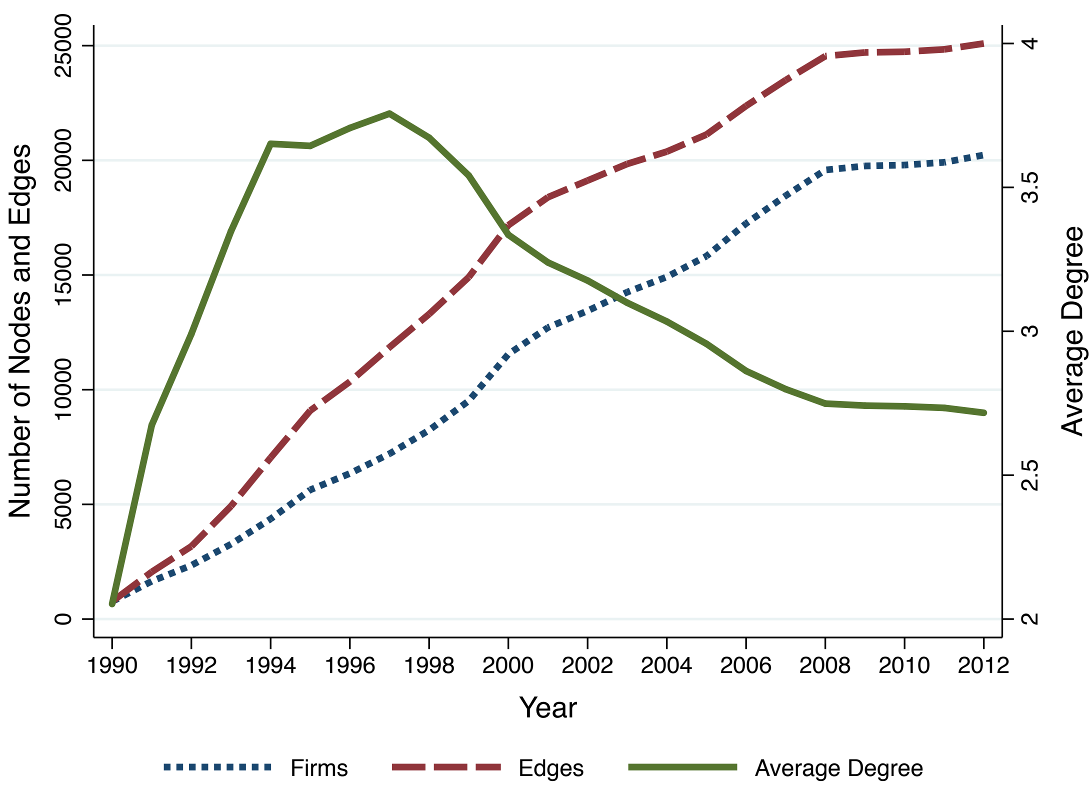


Figure 6: Evolution of Ecosystem Network Structure

A closer examination of the evolution of alliance types by competitive dynamics

Table 3: Coopetition and Convergence Relationship Types

	Coopetition				Convergence			
	-1997	-2002	-2007	-2012	-1997	-2002	-2007	-2012
Equity and Others	475	1,677	2,252	2,491	1,032	3,878	5,117	5,588
Licensing	106	201	212	213	327	584	619	624
Manufacturing, OEM, Supply Chain	78	221	274	308	283	642	772	820
Technology Transfer	259	316	857	1031	818	1,047	1,722	2,023
R&D and Marketing	1,238	1,518	1,819	1,878	4,305	5,118	5,742	5,862
Joint Ventures	1,346	1,745	1,847	1,909	3,267	4,396	4,595	4,735
Total	3,502	5,678	7,261	7,830	10,032	15,665	18,567	19,652

(see Table 3) reveals that while R&D, marketing, and joint-venture alliances dominated both coopetition and convergence activities in the early phases of the ecosystem, we see a substantial growth in technology transfer and non-equity relationships recently, indicating a possible shift from value exploration to value capturing. This result thus supports the premise of the industry life cycle theory, which suggests that firms collaboratively explore the opportunity space to share resources and reduce risk through alliance formation in the early stage. As the market matures, the emphasis of interfirm relationships is shifted towards knowledge exchange and value capture such as through technology transfer relationships.

Figure 7 shows a cumulative growth heat map of coopetition, convergence, and complexity of the ICT ecosystem. We use size and color of bubbles to differentiate levels of ecosystem complexity. While both coopetition and convergence have increased during our study time frame, two distinct ecosystem phases can be identified. Early on the ecosystem was primarily characterized by a growth in convergence; more recently we are seeing a growth in coopetition. The figure reveals a clear transformation path with convergence saturating around 2000, far earlier than coopetition in 2008. Interestingly, we observe that complexity reached its peak shortly after this inflection point and has slightly declined since then. Given that we use an information-theoretic entropy measure for ecosystem complexity, which emphasizes edge formation and network structure, decreasing ecosystem complexity in recent years suggests that fewer firms enter the ecosystem over time and existing firms with many relationships are accumulating more edges. This network formation phenomenon is confirmed by preferential attachment theory, which argues that new firms are more likely to connect to central firms than to less central ones (Barabási and Albert, 1999).

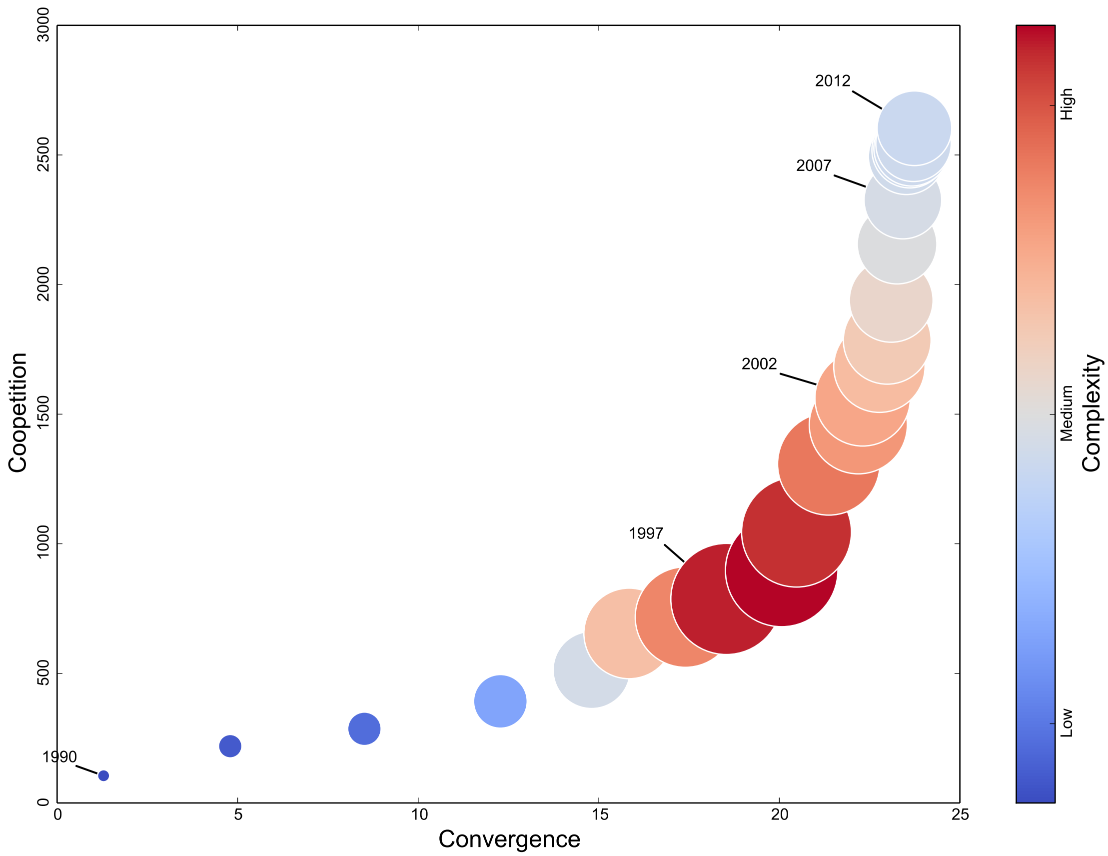


Figure 7: Evolution of Ecosystem Coopetition, Convergence, and Complexity (Bubble size and color reflect ecosystem complexity. Complexity is rescaled by exponential function for visual emphasis.)

These insights understandably lead to the question of how fast the ecosystem is evolving. Figure 8 shows the velocity of both coopetition and convergence. The previously identified difference in saturation timing is also reflected in our analysis of coopetition and convergence velocity. While we see a steady decline in convergence velocity, we observe two velocity peaks for coopetition (in 2000 and 2006) and a slight upward trajectory over the past few years. These findings appear to precede the US economic cycle peaks in March 2001 and December 2007 suggesting potential macroeconomic effects. High convergence velocity suggests that firms were rapidly forming alliances with firms from other ecosystem segments to explore and collaboratively deliver new value propositions to the market. As convergence settled, the velocity of coopetition increased around the year 2000, suggesting that firms sought ways to complement their converged offerings those of their competitors, suppliers, or customers.

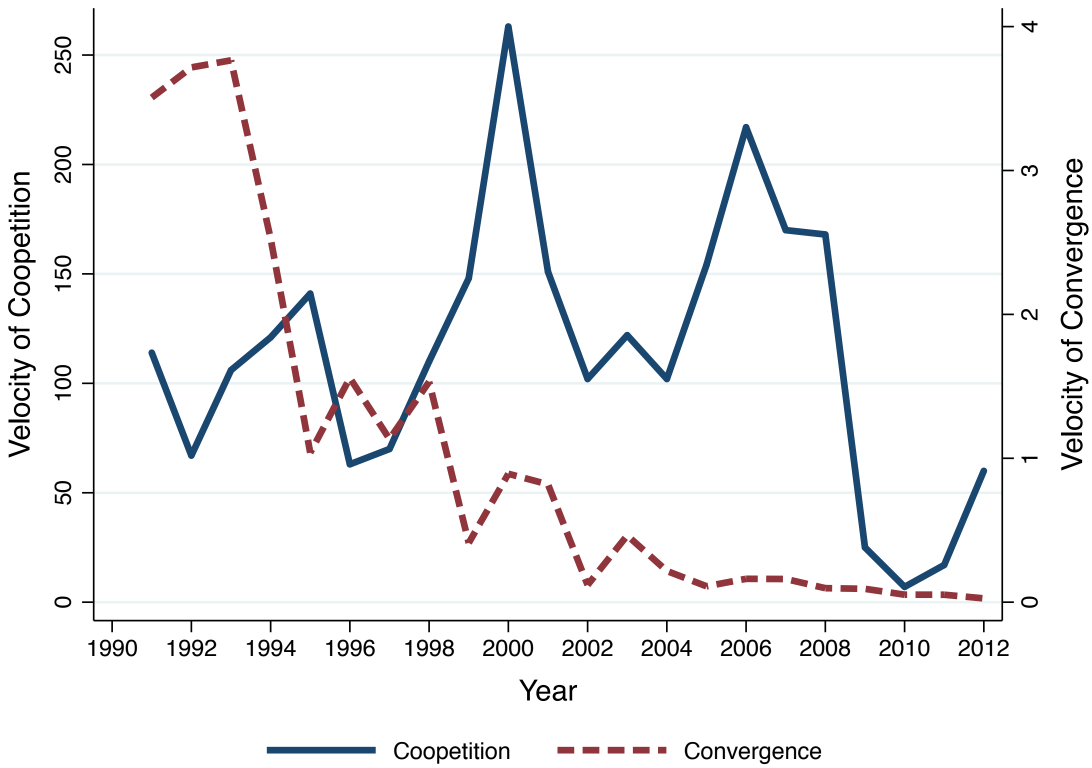
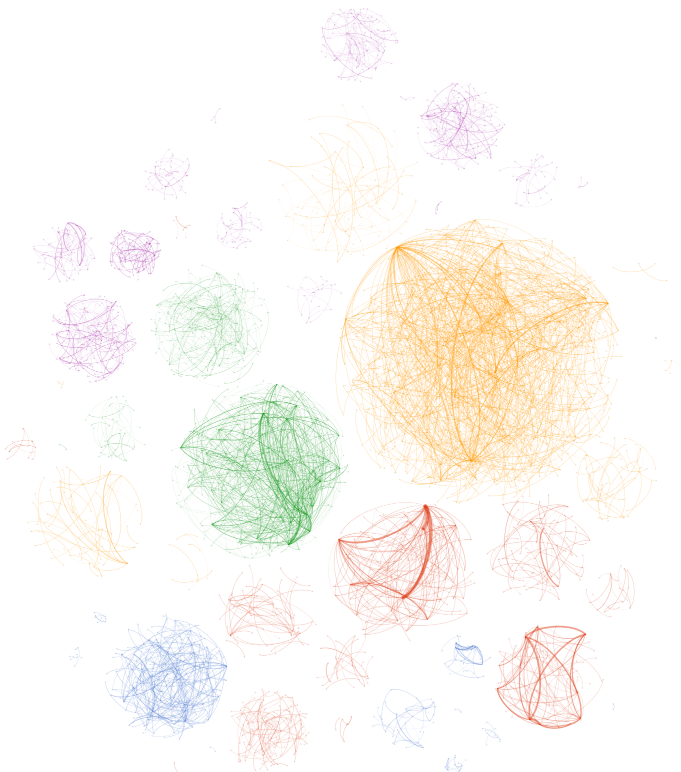


Figure 8: Velocity of Ecosystem Coopetition and Convergence

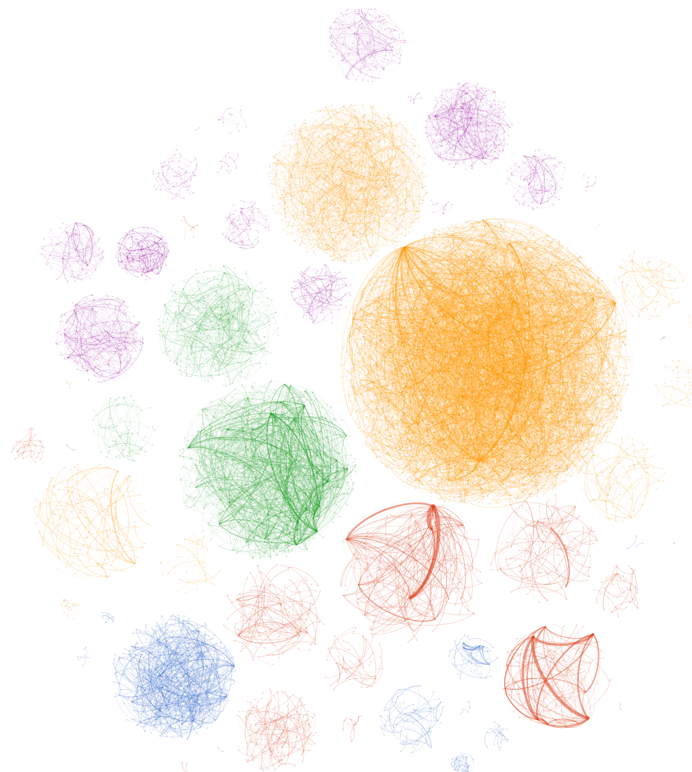
Figures 9a-b provide a closer, visual network perspective of the structural evolution of coopetition in the ICT ecosystem. It should be noted that these figures show only within-segment edges. The figures show that there are some variation of coopetition growth and saturation between segments. For instance, coopetition in the prepackaged software segment (SIC 7372) increased substantially between 2002-2007. Coopetition in data processing services (SIC 7374) on the other hand did not saturate until more recently. Striking is also the rapid rise in coopetition in the media sector (purple). These results highlight that coopetition levels and saturation timing varied across segments and coincide largely with a shift in industry life cycle phases.

We also observe that several ecosystem segments contain some dominant firms. The electronic computers segment (SIC 3571) for instance contains three central players: IBM Corporation, Apple, and Hewlett-Packard Company. Among them, IBM plays the most central role. There are also multiple dominant firms in the household audio and video equipment (SIC 3651) as well as telephone communications segments (SIC 4813), suggesting that these segments are driven by a few large firms.

Interestingly, however, there are segments (of comparable size to the ones mentioned above) in the mobile ecosystem in which the coopetitive structure is far more democratic, including semiconductors and related devices (SIC 3674), radiotelephone communications (SIC 4812), and cable and other pay television services (SIC 4841). Although these segments may have large firms driving and shaping the segment, the alliance structure is relatively more evenly distributed. Together, these visualizations highlight that varying levels of coopetition exist in the ICT ecosystem.



(a) -1997



(b) -2012

Figure 9: Visualization of Structural Evolution of Coopetition

The coopetition visualizations presented in Figure 9 can be further examined by the change in the maximum size of coopetition "pocket". From a graph theoretic perspective, a pocket of coopetition refers to a connected component within each segment. Since we consider firms in the same (four-digit SIC code) segment as competitors, the maximum size of coopetition pocket represents the extent of coopetitive relationships in a segment. The larger this number is, the greater the level of coopetition in the segment. Figure 10 shows the evolution of the maximum size of coopetition pocket. P_0, P_1, P_2, P_3 represent the four cumulative periods of 1990-1997, through 2002, through 2007, and through 2012, respectively. The top panel shows the baseline maximum pocket size for each segment, while the bottom three panels show relative change from the previous period. The top five relative changes for each period are marked by shaded bars in the bottom three panels. The baseline panel highlights that some segments do not engage in any coopetitive activities. The relative change panels reveal that the hardware component sector (blue) is particularly eminent during the early phase while the software sector (orange) has substantial coopetition growth between 2002-2007. More recently, the top driving sectors are distributed across all sectors. The prepackaged software segment (SIC 7372) especially has grown remarkably over the entire time frame, even considering its large baseline size, suggesting that many firms in the segment are engaged in coopetitive activities.

Figures 11a-b provide a segment-level network visualization of the structural evolution of convergence in the ICT ecosystem. The figures clearly reveal that convergence occurred rapidly in the early phases and has slowed down or remained constant in recent years.

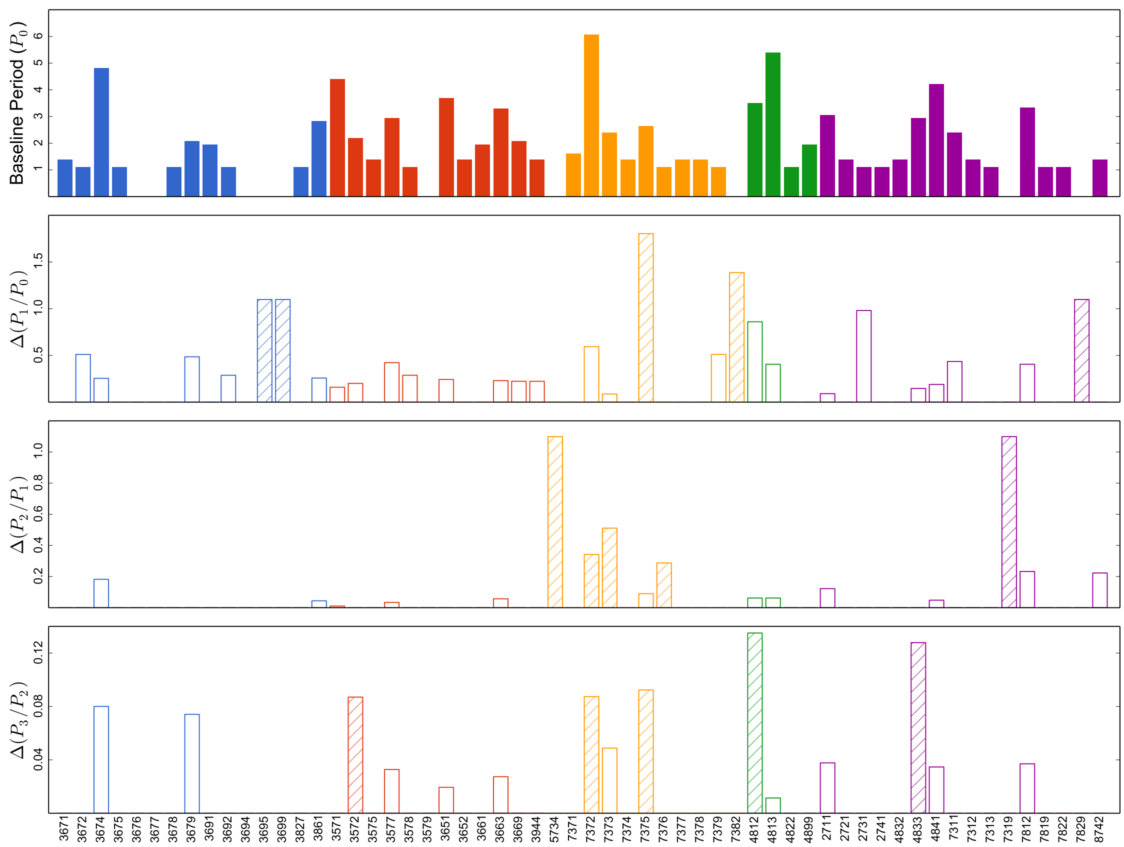
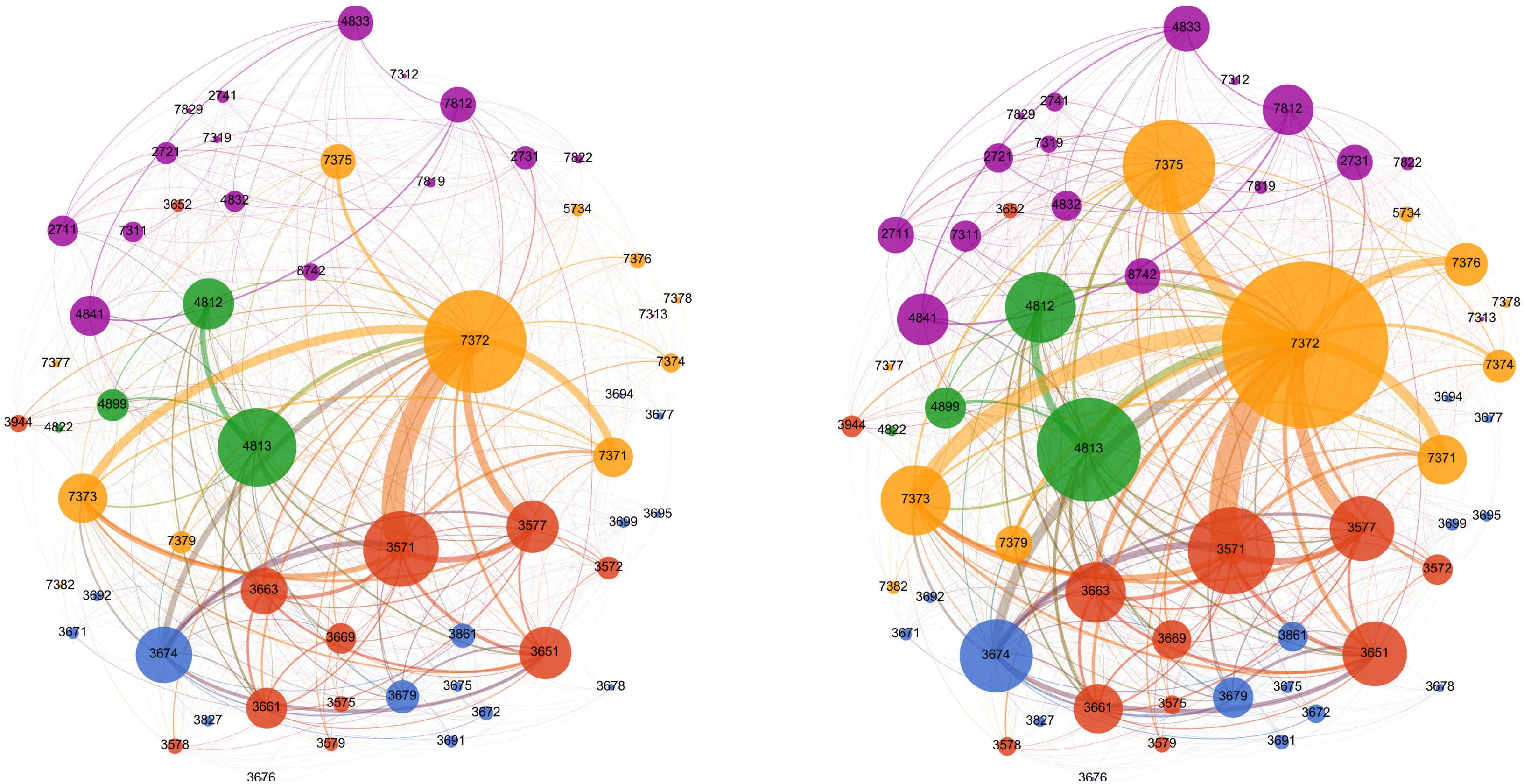


Figure 10: Maximum Coopetition Pocket Size by Segment



(a) -1997

(b) -2012

Figure 11: Visualization of Convergence Evolution

The relative position of segments to each other reveals the growing interdependencies between different sectors. The software sector (orange) is clearly the most central in the ICT ecosystem and acting as the gluing sector that ties together the hardware equipment (red), telecommunications (green), and media sectors (purple). The hardware components sector (blue) is closely connected to the hardware equipment sector. The media sector is more closely linked to software and the telecommunications sector.

The relatively largest growth in segment size over our time frame is experienced by the information retrieval services (SIC 7375). As the ICT ecosystem is becoming increasingly data intensive and dependent, the importance of this software sector segment is becoming more apparent. It is therefore no surprise to see it closely positioned to the segments in the media sector.

When comparing the nature of the media sector from 1997 until now, we can also see that the media sector has grown substantially in size, suggesting that the relative influence and importance has also grown.

Perhaps one of the most striking observations from these network visualizations is that the inter-segment network was quite sparse in the early days; in more recent years the network has not only become more dense, but also more intense, suggesting a greater convergence and thereby knowledge exchange between segments. Figure 12 provides a detailed, matrix representation of the state of ecosystem convergence. The cells represent whether two segments are engaged in inter-segment relationships. The darker the shade of the cell, the more intense the convergence between segments. Within-sector cells are colored following our consistent color scheme, while cross-sector edges are marked in gray. The matrix reveals that the hardware component sector (blue) has two or three central segments connect to other segments; segments in all other sectors are closely connected to each other. The hardware component sector is closely converged with the hardware equipment sector (red) and sparsely converged to the media sector (purple). On the other hand, hardware equipment, software (orange), telecommunications (green), and some segments in media sector are closely connected to each other. Note that some segments[2] including are particularly well converged with most of the other segments in the ecosystem, suggesting that a few segments drive ecosystem convergence.

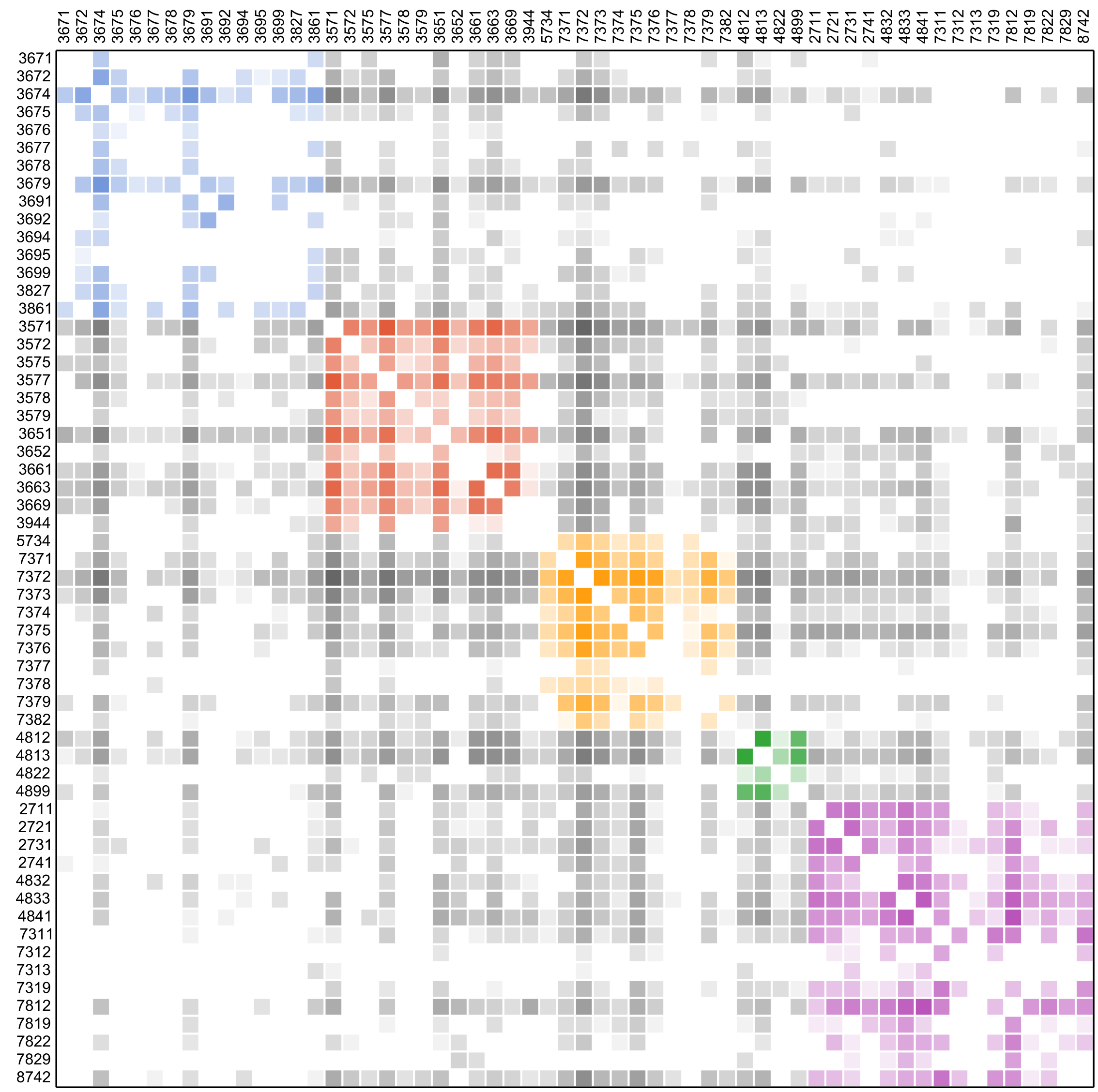


Figure 12: Ecosystem Convergence Matrix (1990-2012)

[2]Representative SIC codes include 3674, 3679, 3571, 3577, 3651, 3661, 3663, 3669, 7371, 7372, 7373, 4812, and 4813.

2.5 Conclusions and Policy Implications

All modern companies struggle with survival in the face of rapid socio-technical change. Quantification and visualization of ecosystems is an important step towards understanding the evolution of industries and the factors affecting this evolution. Rather than using perceptual measures, it provides a more objective foundation critical for managerial sense and decision making. Moreover, it also enables a comparative analysis of patterns within and across industries as well as a way to answer foundational business ecosystem questions of integration, diversification, first-mover advantage, and firm entry and exit.

This study focuses on quantifying and visualizing the competitive dynamics of the ICT ecosystem. In particular, we define and develop graph and information theoretic measures of coopetition, convergence, complexity, and velocity of an ecosystem. Our advanced visual analysis reveals that coopetition and convergence—two key strategic dimensions of opportunity space—have shaped the transformative path of the ICT ecosystem in different ways. While convergence characterized the early phases, coopetition is more prevalent in recent years. Our study also shows that while segments in the ecosystem have converged, the rate of convergence is decreasing, suggesting a growing level of ecosystem maturity and potentially decreasing importance on formal interfirm relationships. We also find evidence of a declining engagement in interfirm R&D and a growing number of technology transfer relationships, indicating a possible shift from value exploration to value capturing. The management literature has developed theories around the trade-off between value creation and value appropriation (March, 1991; Mizik and Jacobson, 2003; Jacobides et al., 2006; Reitzig and Puranam, 2009). Value creation and exploration are linked with search activities that cover a wide area of the opportunity space. Such distant searches thus involves cross-segment collaboration activities. Value capturing and appropriation are the process of extracting value based on the relatively well-known local knowledge. Therefore, local searches are associated with within-segment collaboration activities. Our conceptualization of convergence and coopetition in this chapter builds on cross-segment and within-segment alliances, respectively. Thus, we interpret Figure 7 as a sign of ecosystem-level shift from value exploration to value capturing activities.

The findings of our study also have several important policy implications. Ecosystem convergence leads to a blurring of traditional market boundaries, which demands new consideration of industry-wide and market segment centric policies (Longstaff, 2002; Fransman, 2010; De Vries, 2011). Given the growing interdependence of market segments, policies in one can adversely impact the other. The ongoing debate of net neutrality, for instance, has had implications for mobile network operators, Internet service providers (ISPs), and content providers. Increased coopetition also creates a shift in market power concentration that alters competition in both the short and long term. Policymakers must therefore carefully assess partnerships between competitors (Bauer et al., 2012). Similarly, the increasing global footprint of the ICT ecosystem has an impact on the formulation of trade policies (i.e. where and how value is created and captured) as well as on the setting of national/global innovation policies (i.e. cross-border partners jointly owning intellectual property (IP)). Further, our ecosystem transformation analysis reveals that the path and velocity of the ecosystem differs across the coopetition and convergence dimensions. Broadly, this has two implications: first, policies must be formulated and implemented in ways to accommodate the pace of change. Second, it provides insight into what area of competition policy must be considered when. Lastly, the evolution of our information-theoretic measure of ecosystem complexity suggests that, with the combination of scale and interdependency, it requires more effort to formulate policies that minimize/reduce unintended consequence impacting the ecosystem. Effective policymaking is thus increasingly challenging.

Our study is not without limitations. First, our data consists of interfirm relationships of predominantly large and well-established firms identified by formal alliance agreements. ICT ecosystem innovation, however, is also driven by small and entrepreneurial firms as well as informal relationships between firms. Thus, the entrepreneurial ecosystem consisting of de novo firms may exhibit structural characteristics and dynamics different from the ICT ecosystem analyzed in this chapter. Second, SIC segment classification, while established and validated, potentially limits the scope of actual industry boundaries. For instance, mobile games may be its own segment and distinct from platforms, but using standard SIC classification, they are both grouped into the prepackaged software segment. Third, the edge weighting scheme from 1 to 5 based on the alliance type may seem arbitrary, although we developed this encoding scheme based on Zaheer et al. (2010). There are other ways to encode edge weights. For instance, we can ignore relationship strength at all and apply uniform edge weight. We believe that the implications and conclusions drawn in this chapter are largely invariant to different edge weighting scheme, but it is worthwhile to examine the sensitivity of the results as future work. Fourth, static visualizations do not effectively portray the real complex nature of ecosystem dynamics. An interactive or animated approach would be beneficial. These limitations represent exciting opportunities for future research. Lastly, a firm's position in the value chain matters. Future research on competitive ecosystem dynamics should thus consider the extent to which relationships are formed with firms upstream or downstream in the value chain.

2.5.1 Practical Implications

Our study has several practical implications. With a rapidly changing business environment, fast product cycles, and decreasing average life expectancy of firms, decision makers are feeling a sense of urgency to find novel ways to understand and manage the complexity of their business ecosystem. This study is a first step in applying a framework of new business opportunity mapping and measurement through the lens of complexity theory in order to provide decision makers with actionable insights about patterns of ecosystem evolution. Specifically, this study provides quantitative metrics and a visual framework with which they can map the structure and velocity of business ecosystems and the competitive dynamics that govern it. Our approach thus enables firms to understand the nature of competitive actions at both the firm and ecosystem level, organize appropriately, and devise appropriate innovation strategies. These novel data-based metrics provide the foundation for strategic analysis of new business opportunities that is not possible using traditional market analysis tools. An extension of our work could include a comparison of individual firm strategies in the ecosystem, allowing us to potentially identify firms that lead or chase markets. Our study also provides a foundation to understand the transformative impact of less visible ecosystem events. For instance, we could examine how peripheral activities influence the strategies of core actors in the ecosystem. These implications are excellent avenues for future research.

We did not expect to see a clear demarcation of eras for the ICT ecosystem transformation. We learned from this study that the ICT ecosystem has grown fast in convergence first before 2000 and its transformation locus has shifted to coopetition afterwards. Moreover, the ecosystem complexity measured by information-theoretic entropy peaked around 2000. This set of findings nicely led to the narrative of the ecosystem shift from value creation to value capturing. We did not expect to have this clear narrative before we actually developed the measures and saw the results.

CHAPTER III

INNOVATION STRATEGY FOR PRODUCTS ON DIGITAL PLATFORMS

3.1 Introduction

The previous chapter overviews the ICT ecosystem and documents the transformation path using network visualization and quantification of coopetition, convergence, and complexity. In this chapter, we dive into the ecosystem to narrow our focus on a specific subset of the ecosystem: the smartphone industry. The benefit of narrowing down the research context is that we can observe the product-level output of firms in the scope. The smartphone industry is a place where manufacturer and platform developer are codependent to each other. Manufacturer produces physical product, while platform developer supplies software that runs the device. The product technical specifications evolve within the configurations that software affords to utilize. This chapter aims to develop a theory that views digital platforms as constraints in the search space where manufacturers explore feasible ways to improve their products.

Innovation is essential for firm survival in product-centric industries (Schumpeter, 1942; Utterback and Suárez, 1993). Product innovation enables firms to gain market share (Robinson, 1990; Banbury and Mitchell, 1995; Klepper, 1996); differentiate and diversify their offerings (Abernathy and Utterback, 1978); facilitate entry into new markets (Helfat and Lieberman, 2002); and adapt to changing business environments (Womack et al., 1990; Brown and Eisenhardt, 1995; Eisenhardt and Tabrizi, 1995). Prior research on product innovation strategy is extensive (Brown and Eisenhardt, 1995; Krishnan and Ulrich, 2001) and has examined a broad spectrum of issues, including ideation and design (Dahl and Moreau, 2002), sourcing (Veugelers, 1997;

Kessler et al., 2000; Ragatz et al., 2003), engineering (Michalek et al., 2005), and marketing (Atuahene-Gima, 1996; Lukas and Ferrell, 2000). Several contemporary forces, however, are transforming the nature of product innovation and challenging existing theories, frameworks, and models (Yoo et al., 2010; Nambisan, 2013).

Technological convergence, for instance, has led to the design and development of increasingly complex products. Through hardware miniaturization, component modularity, and standardization, traditionally separate offerings are now being integrated into a single product. Technological convergence has also changed the way firms design and source. Whereas in the past product components and relevant know-how resided in-house, firms today often co-create offerings with other firms and are embedded in an increasingly global and complex value network (Basole and Rouse, 2008). In an era of convergence, product innovation thus involves a wider search across technological, organizational, and geographic boundaries.

Second, there is an increasing infusion of digital technology into physical products. Many products are now a sophisticated combination of hardware and software. Examples are pervasive and range from phones, cameras, watches, and televisions to appliances, medical devices, toys, and cars (Nambisan, 2013). This has led to the emergence of a layered modular product architecture, which is a hybrid between the modular architecture paradigm of physical product design and the layered architecture of digital technology (Yoo et al., 2010). Within this architectural framework, the physical machinery layer defines the physical material properties of the hardware, while the logical capability layer defines how different physical components will be controlled and maintained. Previous research has primarily examined the physical machinery (i.e., hardware) and largely ignored the logical capability layer (i.e., software) in product innovation (Eaton et al., 2011). Innovation of digital products requires a consideration of both (Yoo et al., 2010).

Third, the logical capability layer, e.g., operating system or software-based platform (Tiwana et al., 2010), has been shown to be of particular importance to the growth, evolution, and transformation of technology ecosystems (Burgelman and Grove, 2012; Basole, 2009; de Reuver et al., 2015). Software platforms connect stakeholders in the ecosystem, enable new value creation, and facilitate a continual refinement and expansion of products (Boudreau, 2012). In fact, entire industries are being formed around digital platforms (Gawer and Cusumano, 2014). Given their importance, it is not surprising that a fierce battle between platforms has emerged. Firms offering software platform-based products must judiciously choose among available platforms, consider the respective benefits of each, and devise an appropriate strategy of whether to attach to a single or multiple platforms (Venkatraman and Lee, 2004).

Lastly, the consumer demand for digitally-enabled products is diverse and enormous (Smith et al., 2001). Relative to products offered in the near past, digitally-enabled products are adopted and, due to obsolescence, often replaced at a much faster rate (Billington et al., 2012). In such high velocity environments, competitive advantage declines in duration (Wiggins and Ruefli, 2002) and firms are required to adjust their strategic postures (D'Aveni and Ravenscraft, 1994; Giachetti and Dagnino, 2014). Prior work has identified various possible strategic actions firms can implement to cope with this competitive intensity within a product line (Bayus et al., 1999; Jiao et al., 2007). Chief among these is the design and development of product families. A product family is defined as a set of similar products that are derived from a common platform and yet possess specific features and functionalities to meet particular customer requirements (Meyer and Lehnerd, 1997). A product family strategy allows firms to reuse proven elements in an offering and achieve economies of scale in order to accommodate an increasing product variety across diverse market niches (Utterback and Meyer, 1993; Robertson and Ulrich, 1998).

In light of these realities, existing product innovation models and frameworks must be revisited. While hardware–software systems have been a topic of research interest (Teich, 2012), there is a dearth of studies examining product innovation strategies of digital platform-centric products (Nambisan, 2013). This chapter seeks to explain how a firm's product family strategy and digital platform choice impacts product innovativeness.

We pursue this question by framing product family and digital platform as concepts in innovation search. More specifically, we argue that a product family represents a "path-constrained" search strategy, while digital platforms represent "areas" in technology design space. For product family, we examine two key operational characteristics: number of product families concurrently offered and size of the product family. In doing so, we recognize that firms may pursue multiple parallel searches and extend existing offerings. For digital platforms, we examine the age of the platform and the extent to which firms concentrate on one or more platforms. Our empirical analysis shows that (1) wider and (2) deeper search with product family, (3) newer platforms, and (4) platform concentration are positively associated with product innovativeness.

Theoretically, our study develops a holistic approach to quantifying product innovativeness, differentiating products that integrate a combination of innovative features and those that actually advance the hypothetical innovation frontier. Our study also extends ideas of search scope, depth, and boundaries/regions in product innovation (Katila and Ahuja, 2002a). Managerially, our research identifies strategies that are associated with product innovativeness in an era of hardware-software systems.

The remainder of the chapter is organized as follows. Section 3.2 and 3.3 provide theoretical background and develop our main hypotheses. Section 3.4 describes methods and data. Section 3.5 presents our results. Section 3.6 discusses implications and limitations and Section 3.7 concludes.

3.2 Theoretical Background

3.2.1 Models of Search Space

Prior research has advocated many different frameworks, models, and approaches to understand how firms innovate. Arguably one of the most dominant paradigms in the management literature is to conceptualize innovation as search, a problem-solving process in which organizations manipulate knowledge to create new products and services (Nelson and Winter, 1982; Fleming, 2001; Katila and Ahuja, 2002a). New product engineers, for instance, search for solutions to technical problems by translating requirements into a set of feasible designs (Frenken and Nuvolari, 2004).

The notion of a technological design space was first introduced by Bradshaw (1992). Technologies embody a large set of design dimensions that interact in complex ways (Simon, 1969). The design space specifies the principal technical dimensions of a technology so that each product is represented by a point in multi-dimensional space (Frenken and Nuvolari, 2004).

Schumpeter (1934) notably argued that innovations can be conceptualized as novel combinations of existing resources. A firm's innovation process thus involves sampling a "space" of technical possibilities by recombining, relocating, or manipulating knowledge within this space (March and Simon, 1958; Nelson and Winter, 1982). This technological space is also often synonymously referred to as a pool or landscape of technical knowledge (Levinthal and March, 1981; Kauffman, 1993).

The NK modeling framework (Kauffman and Weinberger, 1989), for instance, suggests that firms use a bounded, iterative, trial-and-error search for novel combinations of existing building blocks over a complex technological landscape. This biologically-inspired model views the search space as a multi-dimensional landscape in which each point represents a combination or configuration of technological elements along with the associated utility or usefulness (Loch et al., 2003; Fleming and Sorenson, 2004; Murmann and Frenken, 2006).

3.2.2 Search Strategies

Two notions of search are particularly salient in prior work: local and distant search. Search is considered local, or exploitative, when firms solve problems using knowledge that is in the neighborhood of their current knowledge base (Helfat, 1994; Stuart and Podolny, 1996; Fleming and Sorenson, 2004). Distant, or exploratory search, is defined as search behavior that involves deliberate effort to explore knowledge bases away from current ones (March, 1991; Katila and Ahuja, 2002a). Cyert and March (1963) referred to these two strategies as slack search and problematic search. While useful, these definitions are not considered precise for empirical investigations and alternate conceptualizations have been developed (Laursen, 2012).

Katila and Ahuja (2002a) introduced concepts of search depth and search scope. Search depth refers the extent to which firms search within a given knowledge area. By searching a knowledge domain deeply, firms gain an exceptional level of understanding and achieve significant breakthroughs by accumulating a deep but narrow knowledge pool through specialization. The deeper the search effort, the greater a firm's cumulative knowledge and competence in that area (Katila, 2000). As suggested previously, firms are predisposed to search locally, or in other words, in knowledge areas in which they have expertise. Search depth thus refers to a local and exploitative search strategy.

Following Katila and Ahuja (2002a), higher search depth positively impacts product innovativeness through several experience effects. By using the same knowledge elements repeatedly, search errors and false starts are reduced, search routines are established, and searches become overall more reliable (Levinthal and March, 1981). Increased experience within a knowledge space also makes search more predictable, thus search activities can be sequenced more efficiently (Eisenhardt and Tabrizi, 1995). Lastly, repeated usage of knowledge elements leads to a deeper understanding of those elements, allowing firms to find potentially novel combinations that are not apparent to less experienced firms of that knowledge domain. On the other hand, it has been shown that repeated searching in the same area is likely to result only in incremental technological advancements and decreasing the likelihood of "radical" innovations (Mezias and Glynn, 1993; Katila, 2000; Fleming and Sorenson, 2004; Schilling, 2005). Continuous search of familiar knowledge exhausts the potential of finding novel solutions as all possible combination of knowledge elements are ultimately achieved (Fleming, 2001; Kim and Kogut, 1996; Schilling and Green, 2011).

Search scope commonly refers to the breadth of knowledge domains explored and is generally used to describe domains in which the firm lacks prior experience or competence (Katila, 2000; Fleming, 2001; Schilling and Green, 2011). A larger search scope enables firms to recombine unfamiliar or atypical combinations of knowledge yielding greater novel outcomes and pursue a greater number of recombinatorial possibilities, thereby increasing the likelihood of "radical" innovations. While larger search scope increases the likelihood of highly novel or radical solutions, it can also be costly (Cyert and March, 1963; Nelson and Winter, 1982; Kauffman et al., 2000). High scope search is more uncertain, difficult, and outcomes are varied and less successful on average (Fleming, 2001; Katila and Ahuja, 2002a). Searching in knowledge domains where they lack prior knowledge and experience, firms expend more resources and effort to understand that area. As scope increases, the number of interactions of knowledge elements increases and comprehension is diminished due to limited cognitive capacity (Simon, 1978; Schilling and Green, 2011). Uncertainty also increases, as firms do not have the benefit of prior experience (Nelson and Winter, 1982).

Besides searching locally and distant, research has also argued that firms employ sequential and parallel search strategies (Abernathy and Rosenbloom, 1969). Sequential search refers to a focused search approach in which firms are committed to a best evident path and pursuing alternate possibilities only if the original proves unsuccessful. Parallel search on the other hand suggest that firms pursue two or more alternatives simultaneously (Green, 2014). Firms can thus gain both greater search depth and search scope with a parallel search strategy. However, parallel search can also be more costly, as firms must expend more resources to manage and direct them.

Prior research in technology management has shown that successful innovation searches are generally more frequent and distant from what a firm already knows. Firms' tendency however is to do exactly the opposite—search too little and stay local. The prevalence of local search is predominantly explained by the fact that significant effort is required to achieve a certain level of technological competence due to greater risks and uncertainty faced by firms when they search for innovations far away from their current location in the space of technological possibilities.

3.2.3 Search Space Regions and Boundaries

The technological search space can be subdivided in many different ways. Extending the local/distant search concept in a geospatial sense, the search space can be differentiated by geographic boundaries (Almeida, 1996; Ahuja and Katila, 2004). The search space can also be divided by knowledge ownership respective to the search firm. (Katila and Ahuja, 2002b) suggests that knowledge spaces have internal and external sectors: the former in which knowledge is created by the search firm and the latter in which knowledge is created by others (Mansfield, 1988; Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002b). This differentiation suggests that firms are innovative either because they translate internal knowledge into new products or capture knowledge spillovers from others. Moreover, Katila and Ahuja (2002b) suggests that given the salience of industry-specific knowledge, the external search space can be further divided into knowledge within and outside the search firm's industry.

Considering dimensions of discovery and viability, Silverberg and Verspagen (2005) suggest that the technological search space be divided into four key regions: (1) technology excluded/infeasible by nature, (2) possible, but not discovered yet, (3) discovered but not viable, and (4) discovered and viable. The fundamental idea behind these four spaces is that not all regions have an equal likelihood of being pursued, discovered, or explored. Boundary regions can also be related to the nature of knowledge—for instance boundary spanning between science and technology knowledge. Studies have shown that ideas are more likely to be high impact when they are the result of a successful connection forged between seemingly disparate bodies of knowledge (Uzzi et al., 2013).

3.2.4 Product Innovativeness

The primary motivation of navigating through the search space is to find locations and regions that generate innovative products. An innovative new product is the cornerstone to success in many industries (McNally et al., 2010). Product innovativeness, for instance, has been shown to have significant influence on a range of important performance characteristics, including cycle time (Ali et al., 1995), new product development performance (Kleinschmidt and Cooper, 1991), product success (Calantone et al., 2006), speed to market (Fang, 2008), and design quality (Swink, 2000).

Despite a rich body of research (see (Avlonitis et al., 2001; Danneels and Kleinschmidtb, 2001) for excellent reviews), there is no single agreed upon definition or measurement of what really constitutes product innovativeness. Innovativeness is often defined as newness (Garcia and Calantone, 2002), meaningfulness (de Brentani, 1989), or discontinuity (Garcia and Calantone, 2002). Regardless which definition is used, an assessment demands a consideration from whose perspective it is considered innovative. While most studies surprisingly do not explicitly distinguish the innovativeness perspective (Danneels and Kleinschmidtb, 2001), several scholars have suggested that a product can be "new" to the world (Cooper and Kleinschmidt, 1993), to the market (Heany, 1983), to the firm (Swink, 2000), or even to the customer (Ali et al., 1995).

Product innovativeness, however, is not merely a binary assessment. Prior work has thus examined the degree or extent of product innovativeness. Many studies use a dichotomous approach, suggesting that product innovativeness can be incremental/radical, evolutionary/revolutionary, or discontinuous/continuous (Avlonitis et al., 2001). Kleinschmidt and Cooper (1991) argued for a triadic categorization, distinguishing between high, moderate, and low innovativeness and suggesting characteristics for each. Henderson and Clark (1990) offered a typology based on an innovation's impact on core design components and relationships between them, suggesting that product innovativeness can be incremental, architectural, modular, or radical in nature.

3.3 Hypotheses Development

Building on these theoretical foundations, we argue that two contemporary phenomena in hardware–software systems require further attention in the study of innovation search. Specifically, we theorize that a firm's choice in product families and digital platforms influences the outcomes of its innovation search. The following sections elaborate on these.

3.3.1 Product Family and Innovation Search

Manufacturers are continuously searching for ways to both expand their product lines and differentiate their product offerings in order to meet the ever-changing market expectations (Ho and Tang, 1998). Previous studies have shown that designing and developing product families is a particularly effective means to achieve economies of scale necessary to accommodate increasing product variety across diverse market segments (Utterback and Meyer, 1993; Cottrell and Nault, 2004). More broadly, by thinking in terms of product families, firms can increase market share and create competitive advantages (Kekre and Srinivasan, 1990; Pine, 1999; Krishnan and Ulrich, 2001).

Pending the functional perspective taken, different interpretations of product families exist (Jiao et al., 2007). From a marketing and sales perspective, a product family describes the various sets of features and functionalities firms have used to target different customer groups. From an engineering perspective, a product family represents a configuration of different components and technologies into a feasible design. Product family strategies are particularly common in assembly industries, such as consumer electronics, computers, and automobiles (Sundgren, 1999; Gawer and Cusumano, 2002), as exemplified by products such as Sony's Walkman®(Sanderson and Uzumeri, 1995) or Black & Decker's power tools (Meyer and Lehnerd, 1997).

Meyer and Lehnerd (1997) define a product family as a set of similar products that are derived from a common platform and yet possess specific features and functionalities to meet particular customer requirements. Individual products within a product family are commonly referred to as a family member or product variant (Jiao et al., 2007). Product variants share designs, components, and other assets (Utterback and Meyer, 1993; Robertson and Ulrich, 1998; Krishnan and Gupta, 2001). Previous work distinguishes between two classes of product families, namely modular and scalable. In a modular product family design, different modules are added or substituted to a common core to develop different products. In a scalable (or parametric) product family design, key product parameters are varied (e.g., "stretched" or "shrunk") to satisfy a range of customer needs (Simpson et al., 2001; Jiao et al., 2007). By reusing existing elements in new product variants, firms can not only accrue cost benefits, but also reduce development risk and system complexity, improve the ability to upgrade products, and leverage their existing manufacturing processes (Sawhney, 1998; Jiao et al., 2007).

In terms of innovation search, we posit that a product family represents a search path of related functional, generational, and compositional elements (see Figure 13). When developing a new product variant, firms do not search across the entire innovation search space, but instead are constrained to regions related to the search path associated with that product family. Scalable product family configurations involve local search exclusively, refining and improving existing designs. Firms exploit existing knowledge by scaling or shrinking design parameters. Breakthrough innovations are less likely to occur. Modular product family configurations may involve both local and distant search as firms may replace existing modules for others. A device manufacturer for instance may replace alternative radios in a smartphone design or use different display technologies, targeting entirely different market segments, use cases, or customer bases.

3.3.1.1 Number of Concurrent Product Families

While the design and development of a single product family may involve local search, introduction of multiple families may involve greater scope of search, including exploratory distant search. Firms may experiment with new technological configurations and designs to target new market segments. As product families will most likely vary in their market target and functionalities, they will also traverse and occupy different regions of the innovation space to deliver differentiated value.

By adding more product families, firms increase the scope of their search (Katila and Ahuja, 2002a). Search scope describes how widely a firm explores new knowledge. It has been shown that search scope positively affects product innovativeness as it expands the knowledge pool by adding new variations (March, 1991) and enhancing recombinatory search (Fleming and Sorenson, 2001). Multiple product families thus represent multiple search paths in innovation space. Firms create multiple product families to achieve product differentiation and address different market segments

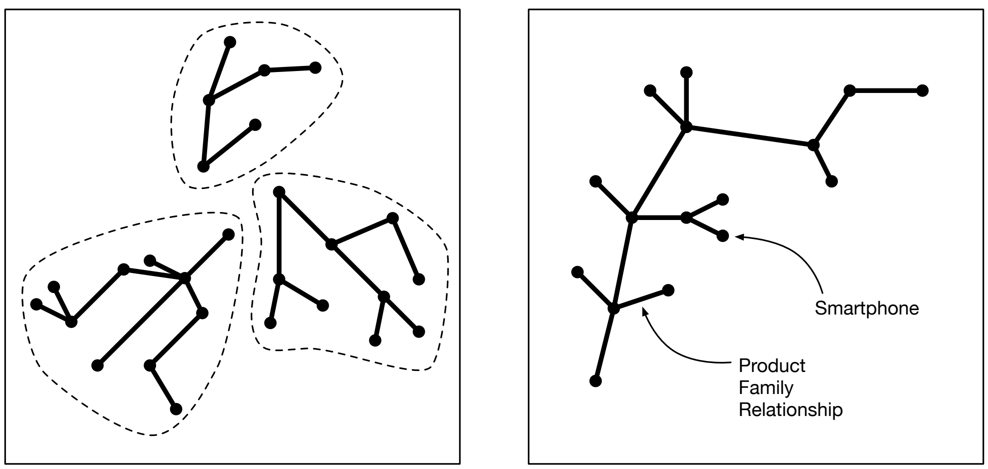
(Halman et al., 2003). The idea of pursuing multiple product families also corresponds to the line of thinking that parallel search is particularly beneficial in complex technology landscapes (Kornish and Ulrich, 2011). Firms pursuing multiple product families thus explore more of the design space, can learn and gain insights from the different search paths pursued, and accrue knowledge spillover benefits which can in turn be implemented into innovative new product offerings. A larger number of product families allow manufacturers to experiment with and explore novel configurations of different features and functionalities, increasing the likelihood of creating more innovative products.

Hypothesis 3.1 *Ceteris paribus, the number of concurrently developed product families will be positively associated with product innovativeness.*

3.3.1.2 Size of Product Family

A second innovation search dimension is search depth (Katila and Ahuja, 2002a). Search depth refers to how deeply a firm reuses its existing knowledge. Nelson and Winter (1982) showed that incremental product changes build on past practices and technique. Dosi (1982) emphasized that technological innovation is both physical and conceptual, consisting not only of parts and components, but also of a set of accumulated knowledge, techniques, and skills. New products may leverage older products directly through reuse of physical components or indirectly through cumulative learning (Jones, 2003). Prior studies have shown that increase in search depth can positively impact product innovativeness, by reducing the likelihood of errors, making search more reliable and predictable, and creating a deeper understanding of the underlying technological concepts (Levinthal and March, 1981; Winter, 1984; Katila and Ahuja, 2002a). Firms increase search depth by extending the size of the product family. New product variants build on existing members of the product family. The creation of new product variants, through either product family configuration approach, reuses a firm's existing knowledge. The greater the size of the product family, the deeper the knowledge reuse. Larger product families allow firms to realize economies of scale and scope (Axarloglou, 2008; Giachetti and Dagnino, 2014). By extending the size of product families, firms continuously refine, tune, and improve technological designs, ultimately leading more innovative products. More formally,

Hypothesis 3.2 *Ceteris paribus, the size of the corresponding product family will be positively associated with product innovativeness.*



(a) Count (b) Size

Figure 13: Product Family in Search Space

3.3.2 Platform and Innovation Search

Platforms are pervasive in today's business environment (Gawer and Cusumano, 2002; Evans et al., 2006). While there is no universal definition, research in the management literature has primarily conceptualized platforms either as markets (economic perspective), technological architectures (engineering design perspective), or enablers of digital products and services (information systems perspective) (Gawer and Cusumano, 2014; de Reuver et al., 2015). In this study, we adopt the definition by Tiwana et al. (2010) that a platform represents the logical capability layer, or "extensible codebase of a software-based system that provides core functionality shared by the modules that interoperate with it and the interfaces through which they interoperate." Such digital platforms play a particularly important role for products in the information and communication technology ecosystems (Basole, 2009; Boudreau, 2010). Given their importance, it is not surprising to see fierce competition between platforms for market share (Gawer and Cusumano, 2008; Eisenmann et al., 2011). The battle between platforms in the personal computer industry is particularly well documented (Gawer and Cusumano, 2002; Bresnahan and Greenstein, 2003). A fierce battle now also exists in the rapidly emerging mobile device and video game console industry (Venkatraman and Lee, 2004; Zhu and Iansiti, 2012).

We argue that a digital platform demarcates an already discovered, viable, and potentially untapped technology region in innovation search space (see Figure 14). Given that competing platforms often have many common and some unique capabilities, we further posit that the respective search regions enabled by these platforms have some degree of overlap as well as fill unique regions in the space.

The conceptualization that platforms enable regions in innovation space builds on ideas proposed by Katila and Ahuja (2002b) and Silverberg and Verspagen (2005) that innovation search spaces can be distinguished by technological boundaries and that some knowledge spaces are enabled by entities external to the search firm. Software platforms facilitate new technological capabilities and are generally provided by platform providers. Moreover, this conceptualization is appropriate if we consider knowledge recombination as a bounded problem-solving process. Some knowledge recombinations are simply infeasible due to physical constraints or conflicts; others may not be possible due to a lack of technological enablement. Metaphorically, it could be suggested that platforms provide a "spotlight" for firms to identify feasible innovation search regions.

3.3.2.1 *Platform Age*

It is well documented that the age of the knowledge space searched by a firm has an influence on product innovativeness (Sorensen and Stuart, 2000; Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002b). On the one hand, older knowledge spaces are more established, reliable and valuable than more recent ones (March et al., 1991). Firms have had time to access, learn, and understand the consequences of elements contained in older knowledge spaces, thereby decreasing the risk of costly errors and increasing innovation search productivity (Levinthal and March, 1993; Katila and Ahuja, 2002b).

Conversely, researchers have argued that firms should rather search in more recently developed knowledge spaces, because, as knowledge spaces age, they become obsolete and no longer match the market demand (Eisenhardt, 1989; Thompson, 1967). Referring to it as the competency trap, Sorensen and Stuart (2000) found that firms building on to a large extent on past knowledge bases often miss the opportunity to innovate with recent and potentially more rewarding knowledge. In contexts where innovations occur rapidly, older knowledge spaces are particularly likely to deplete, eventually exhausting all possible knowledge combinations. Search in old knowledge spaces hurts finding new innovations; firms searching in recent knowledge spaces avoid obsolescence.

Following our proposition that platforms determine feasible innovation search space regions, we argue that a platform's age influences the boundary of that space. Platforms as well as their capabilities and functionalities evolve over time. Newer platforms build on existing knowledge and advance the boundary of the innovation search space, enabling recombination of unexplored and viable knowledge elements. Older platforms represent older knowledge spaces, which have likely been searched exhaustively and provide fewer opportunities for novel knowledge recombinations.

Hypothesis 3.3 *Ceteris paribus, platform age will be negatively associated with product innovativeness.*

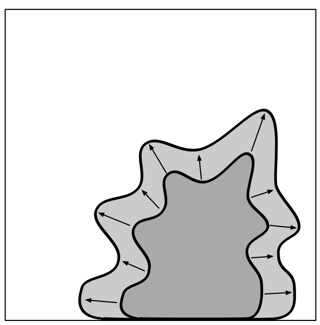
3.3.2.2 Platform Concentration

Contemporary technology ecosystems are characterized by the presence of multiple software-based platforms (Evans et al., 2006; Tiwana et al., 2010). Firms must often make deliberate choices choosing among available software platforms, taking various enabling capabilities and characteristics provided by each into consideration. Some firms may choose to use a single platform for all their product offerings, while others may choose multiple. Prior work in engineering design and technology management has offered several different explanations for how firms choose platforms including network effects, economic potential, incentives, and platform attractiveness.

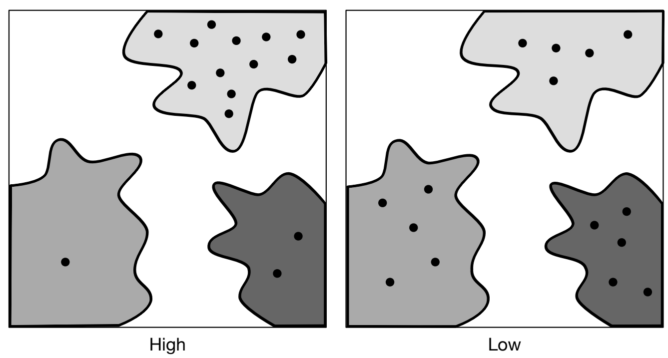
In terms of innovation search, a firm's platform choice corresponds to which and how many search regions it has available for its search initiatives. Firms choosing a single platform limit their search scope. But given that all search initiatives will be targeted into a single search area, their understanding of that area deepens substantially. Multiple platforms on the other hand widen the search scope. It allows firms to gain new knowledge, insights, and experience about novel recombinations. These insights can lead to important knowledge spillover effects useful for other search initiatives. However, with multiple platforms, firms must expend more resources in order to search a diverse set of knowledge spaces, which can be costly, uncertain, risky, and thereby lead to less innovative outcomes. Given resource constraints, firms choosing multiple platforms must therefore decide how to distribute its search initiatives across these multiple search regions.

We refer to the distribution of search initiatives as platform concentration. The more distributed a firm's search initiatives across the chosen platforms, the lower its platform concentration. The more targeted the search initiatives for a region, the higher the platform concentration. Higher platform concentration implies that a firm has a higher search depth in a particular platform region. There are several benefits of platform concentration. Platform concentration enables firms to gain greater understanding of that knowledge space. Consequently, it enables firms to eliminate bad and focus on good combinations. Over time, platform concentration creates competence and experience that helps with future search initiatives.

Hypothesis 3.4 *Ceteris paribus, the degree of platform concentration will be positively associated with product innovativeness.*



(a) Age



(b) Concentration

Figure 14: Digital Platform in Search Space

3.4 Data and Methods

3.4.1 Research Context

This study uses the smartphone industry to test the proposed hypotheses. The smartphone industry has a number of characteristics that makes it particularly suitable for studying strategies related to product family, digital platforms, and product innovativeness. First, the smartphone industry is arguably one of the most rapidly evolving technological domains of recent years, characterized by a deep intrinsic intertwining of innovative hardware and software (Anonymous, 2015). Over the past decade we have witnessed an explosive growth of smartphones. Smartphones have evolved from very expensive, clunky monochrome devices to sleek, converged, mass consumer market devices. One of the first “Swiss Army Knife” phones was the IBM Simon released in 1993. It had functions such as a fax, a personal data assistant (PDA), a pager, and even featured a touchscreen that could be used to dial phone numbers. Since then many transformational advances in mobile phone technology and product design have occurred, including the Nokia Communicator 9000, which featured a slide-out QWERTY keyboard, Research in Motion’s BlackBerry 5810, which provided the ability to read e-mail and surf the Web, or the Palm Treo, which integrated PDA functionalities and a handwriting recognizing system in a mobile phone with expansion slots and an upgradeable operating system (OS). Unquestionably, a landmark event in the history of smartphones was the launch of the Apple iPhone in 2007. The iPhone integrated a touchscreen display with one of the best web browsing experiences on a mobile device. Today’s leading smartphones are largely a derivative of this innovative product. Technologies used in smartphones today are highly modular and interdependent. Smartphone manufacturers must make careful choices in selecting and integrating the right combination of technological components to produce a novel and successful product. This choice requires search in a continuously expanding, but constrained technology design space. New sensors, for instance, can only be added to the device if the appropriate mobile central processing unit (CPU) speed is available. Likewise, a camera module is only of value if the built-in storage is reasonably large enough relative to the camera resolution.

Second, smartphones, by definition, are driven and enabled by digital platforms (i.e., operating systems). Over the past decade we have seen a fierce battle for market share between a diverse set of mobile platforms. Only a decade ago, Symbian and Blackberry OS were the leading platforms. Today, smartphone manufacturers can choose from several more, including iOS, Android, Windows Phone, or a Linux-variant. Platform versions are regularly updated to keep up with technological advances and evolving needs. Smartphone manufacturers are forced to make deliberate platform choices, including a consideration of whether to develop their own proprietary platform, which platform(s) to launch new smartphone models on, and whether to diversify or concentrate their platform portfolio. The digital platform choice is thus an important strategic decision a smartphone manufacturer must make to have its product adopted by consumers (Cusumano, 2010).

Finally, unlike any other consumer electronics category, smartphone models are developed and launched at an unprecedented pace. This is in part triggered by the insatiable appetite of the market for new gadgets as well as the growth in global demand. In order to meet these changing market needs, manufacturers must make careful product decisions and consider ways to differentiate their offerings. To differentiate offerings and rapidly develop new products, the use of product families is a pervasive phenomena in the smartphone industry.

3.4.2 Sample

To the best of our knowledge, there is no single public data source that provides a comprehensive, integrated, and curated dataset on smartphones. We thus carefully retrieved, matched, and triangulated data from two of the most well-established consumer websites, namely PhoneArena[1] and PDAdb[2]. PhoneArena provides detailed technical specification data on smartphones including product announcement and release dates; PDAdb provides complementary information, including product codenames, operating system versions at the time of launch, and CPU chipset models.

As smartphone model names occasionally differed and there was no single unique identifier, we paid close attention to matching smartphone models between the two

[1]http://www.phonearena.com
[2]http://www.pdadb.net

data sources. Our initial dataset included 1,331 smartphone models from 79 different manufacturers released between 2000-2012. Following Katila and Ahuja (2002a), we dropped products with identical model names and technical characteristics, but were marketed for different geographic regions (e.g., "American Version"). We also dropped rumored but never released models from our sample. Our final sample then reduced to 1,092 unique smartphone models.

We extracted detailed technical specifications including *physical design* (width, weight), *display* (size, resolution, pixel density, panel type), *computing power* (CPU clock speed, number of cores, random access memory (RAM) size, storage size), *battery life* (battery capacity, talk time, stand-by time), *connectivity* (cellular network speed, Wi-Fi standard, Bluetooth version), *camera* (resolution of main camera, resolution or existence of sub camera, resolution of video), and types of *sensors*. We also identified each smartphone's *digital platform* (Android, iOS, WindowsPhone, etc.) and *platform version*[3].

Table 4 presents a descriptive summary of all technical specifications. Figure 15 shows the technological evolution (x-axis denotes time; y-axis presents standardized z-score values). Several observations can be made. First, there are two different modes of evolution: exponential and linear. For example, physical (thickness and weight) and battery properties (talk time, stand-by time, capacity) have been decreasing and increasing linearly, respectively. Following Moore's law, computing properties have been increasing exponentially. Second, technological specifications generally improve

[3]Most technical features are well understood; others demand some more explanation. Battery capacity, for instance, is an indicator of how much charge, measured in milliampere-hours (mAh), a smartphone can hold. Talk and stand-by time (both measured in minutes) consider the power efficiency of the circuit design. It is possible that smartphones with identical battery capacities can have different talk times because one is more efficiently designed. Coding quantitative technical specifications is straightforward. Weight is measured in grams, while screen size is measured in inches. More complicated is the coding of qualitative technical specifications, such as display panel type, Wi-Fi standard, or Bluetooth version. For display panel type, we used the time (in years) since our sample start date (2000) when a certain display panel type was first used in a smartphone model as a proxy of the technological advancement of the panel type. For the different connectivity standards, we used the documented speed of the standard as a proxy for technological superiority.

over time but there are time periods when improvements plateau or reverse in trend. Average thickness, for instance, increased from 2002-2004; average storage memory plateaued from 2009-2011; average stand-by time stalled from 2009-2011 while battery capacity kept increasing during the same period. Lastly, and related to the prior observation, features have differing take-off timings suggesting clear demarcation of new introduction, fundamental change, or even popularity. Sensors are virtually non-existent in smartphones prior to 2007, but increase significantly after that. Average wireless speeds jumped post-2010. Diagonal display sizes increased rapidly after 2008. Together, these findings support a well-established assumption, namely that manufacturers must make design trade-offs when adding or improving one feature for another.

Table 4: Descriptive Statistics of Technical Specifications of Smartphones in the Sample

Group	Innovation Dimension	N	Mean	Std. Dev.	Min	Max
Physical	Thickness	1,073	14.39	4.11	6.70	41.00
	Weight	1,052	133.34	30.12	55	490
Display	Display Diagonal	893	3.35	0.68	1.80	5.55
	Resolution	1,069	231,067	216,112	16,000	2,073,600
	Pixel Density	880	206.78	54.44	113	441
	Display Panel Type	998	2.45	3.28	1	12
Computing	# Cores	808	1.19	0.49	1	4
	CPU Clock Speed	842	766.09	377.07	33	2,000
	RAM	775	403.83	360.83	1	2,048
	Storage	644	4.90	7.69	0	64
Battery	Talk Time	976	6.67	3.43	2	35
	Stand-by Time	954	324.29	152.10	48	1,090
	Battery Capacity	1,008	1,374.41	311.69	500	3,300
Camera	Main Camera Resolution	1,020	4.03	2.37	0.10	16.00
	Video Resolution	475	843,904	702,851	25,344	2,073,600
	Sub Camera Resolution	244	0.77	0.58	0.10	2.10
Connectivity	Cellular Network Speed	1,050	13.12	25.16	0.06	100.00
	Wi-Fi Standard Speed	845	284.49	278.37	11	600
	Bluetooth Version	928	2.27	0.65	1.10	4.00
Sensors	# Sensors	1,092	2.71	2.05	0	7

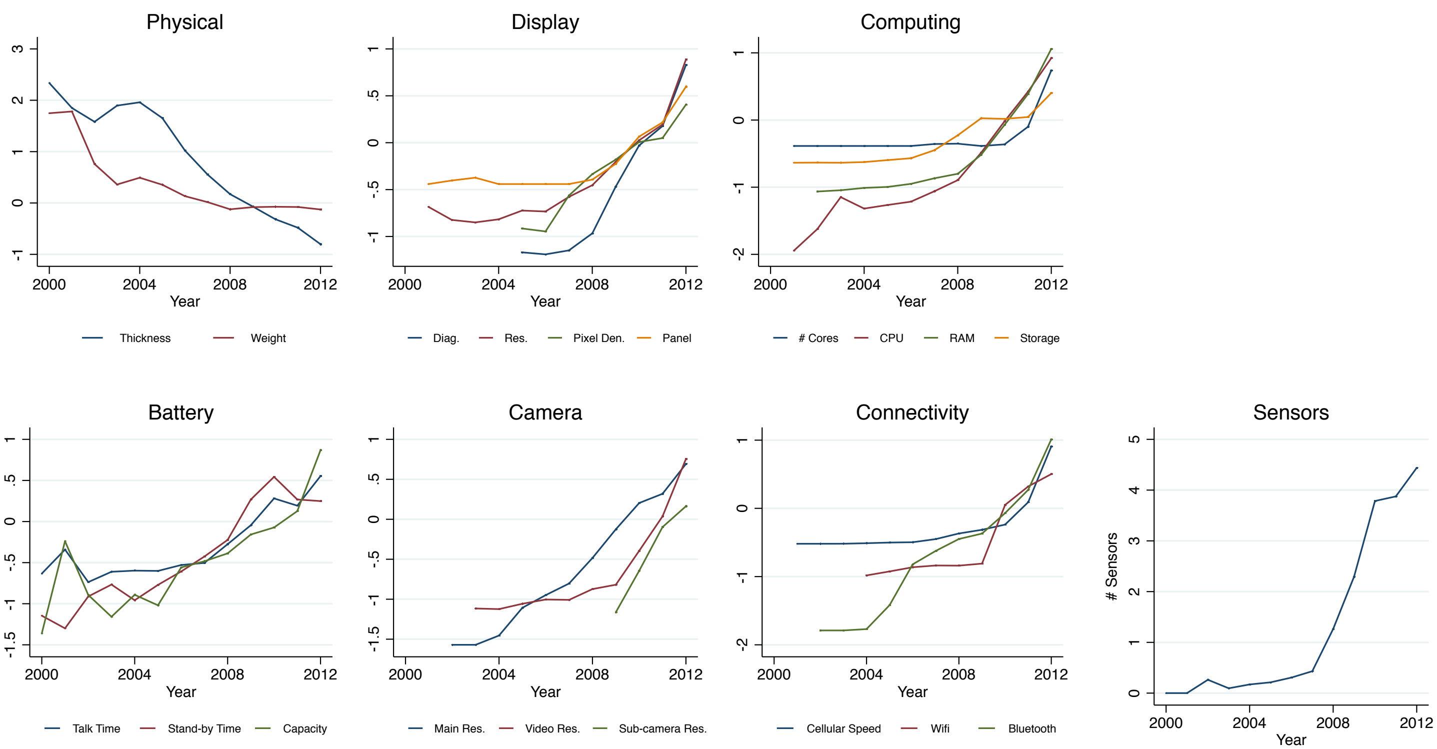


Figure 15: Technological Evolution of Smartphones 2000-2012

3.4.3 Variables

3.4.3.1 Dependent Variables

We consider *product innovativeness* as the extent to which one or more smartphone features (i.e., technical specifications) are more advanced (or completely novel) as compared to all previously available models. This definition builds on conceptualization of an innovative new product from Martin and Mitchell (1998) and Katila and Ahuja (2002a). Our study thus considers innovativeness based on a market view perspective. With this core definition, an improvement in any single feature "relative" to all previous smartphones in the market—a faster CPU, improved battery life, or novel sensor—would thus make a smartphone innovative. However, given that a smartphone is a complex hardware–software product consisting of multiple technological features, this view would be limiting. Changes in each feature must be considered jointly to truly capture product innovativeness.

As prior work has pointed out, there are inherent trade-offs between features in complex products (Frenken and Nuvolari, 2004; Murmann and Frenken, 2006). For instance, memory storage size constrains the maximum resolution of a smartphone camera. Likewise, a smartphone could contain a desktop-class speed CPU only when heat and battery is under control. Consequently, to assess the innovativeness of a smartphone, we adopted the notion of an innovation frontier (Lieberman and Dhawan, 2005). The innovation frontier represents a hypothetical "best" smartphone benchmark that integrates the best features and feature levels (e.g., largest battery capacity, lightest weight, thinnest thickness) from all smartphones previously in the market. If a new model surpasses this innovation frontier in any aspect, we consider that smartphone innovative.

Based on expert feedback, two additional requirements have to be taken into account in the development of a product innovativeness index. First, a smartphone surpassing the benchmark in only one aspect must have a lower innovativeness index than one surpassing it in many aspects. Second, the innovativeness index must not be sensitive to the inclusion or exclusion of a single feature. For instance, smartphones will evolve and incorporate new, emerging technologies (e.g., 3D displays) in the future. The index should be flexible and be neither ignorant nor too sensitive to addition or removal of such new technological elements. To allow for these requirements, we doubly abstracted the product innovativeness index by categorizing the smartphone features into logical and equally weighted groups.

Conceptually, our innovativeness index captures how "close" or "distant" features incorporated into a new smartphone model are beyond smartphones currently in the market. Implicitly, this assumes that there is a desired technology evolution direction for each feature. For example, all else being equal, the market will favor a higher clock speed CPU or a thinner/lighter smartphone. For some features, however, the direction can be ambiguous. Length and width preferences are debatable. Consumers valuing mobility may prefer smartphones with a small surface area, whereas others valuing large displays may prefer a long and wide form factor. To avoid such ambiguity, we only included features where there was a clear notion of feature advancement. The final list of groups and associated features included in our index are shown in Table 4. Based on this foundation, the innovativeness of a smartphone i is then computed as:

$$\text{Innovativeness Index}_i = \left(\sum_{G \in \mathcal{G}} \left(\sum_{x \in G} \frac{x_i - \mu_x(t)}{\sigma_x(t)} \right) / |G| \right) / |\mathcal{G}| \tag{7}$$

where G denotes one of the seven feature groups (physical, display, computing, battery, connectivity, camera, and sensors); $|\mathcal{G}|$ is the total number of feature groups and $|G|$ is the number of features in the feature group G; and x corresponds to a specific feature in each feature group (e.g., weight in physical group). x_i thus denotes the technological specification of feature x of smartphone i. $\mu_x(t)$ and $\sigma_x(t)$ are mean and standard deviation of feature x of all smartphones that had been released into the market before time t. In sum, our index computes z-score ($\frac{x_i - \mu_x(t)}{\sigma_x(t)}$) for each feature

x, takes the average within each feature group G, and then computes the average over all seven feature groups $\mathcal{G}$. Feature groups are equally weighted and each feature has the same weight within a group. Using the standardized score (i.e., z-score) in the innovativeness index makes the variable follow the normal curve, which is a desirable property for regression analysis.

Our innovativeness index purposely uses a balanced approach to identify innovative smartphones. However, this approach does have limitation that it does not explicitly capture smartphones advancing the contemporary innovation frontier. Consequently, two possible scenarios may occur. First, a particular model may advance the frontier, but its overall innovativeness may be poor. For instance, a smartphone may have the largest screen size to date, but at the cost of short battery life and substantial weight. Second, a smartphone may be near the frontier, and therefore highly innovative, but never in fact advanced the boundary. To complement the z-score-based continuous innovativeness index proposed in Equation (7), we therefore compute two additional dependent variables. The first is a binary variable of whether or not a smartphone i advanced the innovation frontier in any technological feature group; the second is the number of feature group boundaries a smartphone i advanced outward.

3.4.3.2 Independent Variables

The *number of product families* corresponds to the total count of product families a firm concurrently offered during the previous year with respect to a smartphone's announcement date t. Following our conceptualization, a product family consists of smartphones with similar combination of features. We operationalize membership in a product family using three key criteria. First, manufacturers often explicitly describe products using predecessor–successor relationships. Many products that carry

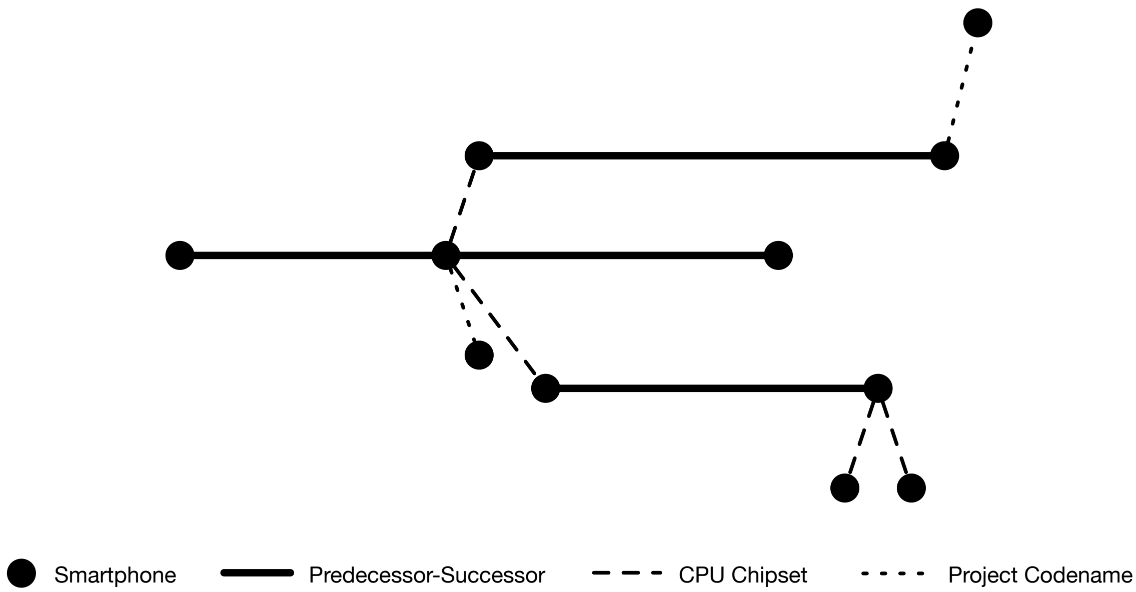


Figure 16: Operationalization of the Product Family Definition

the same model name are part of a flagship series (e.g., Samsung Galaxy S to Samsung Galaxy S II). This convention is often used to signal to consumers that certain products group together. Second, following a technological component perspective, we argue that smartphones sharing the same CPU chipset, and thus possess the same processing capabilities, belong to the same product family. Third, manufacturers frequently use codenames to refer to smartphone models during the design and development process. Smartphones sharing same codenames thus can be considered to belong to the same product family as well. Figure 16 presents a graphical conceptualization of these three practices. Nodes represent smartphone models; edges represent the three product family connectors. A product family then is the entire subgraph (i.e., union of the three criteria) within a manufacturer's product offerings.

The *size of product family* is defined as the total number of smartphones offered within the same product family during the previous year. It thus measures the size of a product family subgraph.

Platform age is defined as the difference (in years) between the product announcement date t and the platform's launch date. Based on the conceptualization that platforms cumulatively build on prior platforms, newer platforms expand the feasible search area.

We measure *platform concentration* of a manufacturer using the Herfindahl-Hirschman Index (HHI). This index is a well-tested and widely used measure that quantifies level of concentration, i.e., how diversified a firm or a particular industry is. For each manufacturer, we first compute shares of smartphones developed for each platform. We then compute the sum of squares of shares for all platforms. A higher concentration measured as high HHI means that a manufacturer focuses on a particular platform; a lower concentration indicates that the firm uses a diversified approach.

3.4.3.3 Control Variables

We include both product- and firm-year-level control variables. First, the *number of products* a manufacturer launched in the past year controls for the prolificity of a manufacturer's product development cycle and schedule. Second, the *number of platform versions* during the previous year controls for how actively a platform is maintained. High frequency of version updating has its trade-offs. Updated platform versions may make previously unavailable regions in search space feasible, however, implementing new versions may also incur learning costs. Third, we control for whether the focal smartphone was developed on a manufacturer's *proprietary platform*. Some manufacturers, such as Apple and Blackberry for instance, maintain their own mobile platforms and develop smartphones only for their platforms. Samsung, on the other hand, has migrated across many different platforms over the past few years, including its own. Lastly, following Kini and Williams (2012), we control for relevant firm characteristics. Since smartphone represents a high-tech industry, we control for *R&D intensity* measured as R&D expenditure divided by total assets. As manufacturing smartphones involves maintaining a global supply chain and other capital-intensive activities, we also control for *capital intensity* measured by capital expenditure divided by total assets. The *number of employees* controls for firm size. All firm-related variables are drawn from Compustat North America or Compustat Global and are recorded at firm-year level. We also include dummy variables denoting whether the manufacturer is from the U.S. and whether the manufacturer is listed in Compustat. Following Kini and Williams (2012), we impute zeros for manufacturers not listed in Compustat.

Table 5 provides summary statistics of all variables and the corresponding pairwise correlation coefficients. Note that the innovativeness index cannot be computed for the first smartphone in the dataset due to lack of benchmark. By definition, the first phone does not have a benchmark of existing smartphones to compare with.

Table 5: Descriptive Statistics and Pairwise Correlations

Variable	Pairwise Correlations and Descriptive Statistics																
Innovativeness Index																	
(Dummy) Boundary Advanced	0.20																
# Boundaries Advanced	0.22	0.89															
# Product Families	0.33	-0.06	-0.06														
Family Length	0.15	-0.02	-0.04	0.09													
Platform Age	0.03	-0.13	-0.15	-0.09	0.26												
Platform Concentration	0.03	-0.04	-0.08	-0.11	0.28	0.24											
(Log) # Products	0.23	-0.10	-0.11	0.64	0.24	-0.01	0.11										
# Platform Versions	0.13	-0.17	-0.18	0.36	-0.13	-0.23	-0.06	0.28									
(Dummy) Own Platform	-0.07	0.04	0.05	-0.24	0.39	0.27	0.33	-0.12	-0.52								
R&D Intensity	0.01	0.09	0.07	-0.12	0.39	0.21	0.23	0.02	-0.37	0.53							
Capital Intensity	0.10	0.08	0.09	0.23	0.04	-0.04	-0.22	0.20	-0.23	0.09	0.05						
(Log) # Employees	-0.01	0.07	0.05	-0.27	0.17	0.15	0.20	-0.19	-0.30	0.41	0.61	-0.09					
(Dummy) US Manufacturer	0.01	0.01	0.01	-0.09	-0.04	-0.06	0.10	-0.13	-0.23	0.28	0.29	0.00	0.38				
(Dummy) Compustat Missing	-0.09	-0.08	-0.08	0.03	-0.21	-0.06	-0.12	-0.05	0.46	-0.25	-0.57	-0.49	-0.42	-0.29			
Year	0.30	-0.27	-0.28	0.39	-0.04	0.07	-0.08	0.33	0.69	-0.29	-0.26	-0.15	-0.16	-0.13	0.38		
Month	-0.04	-0.10	-0.11	0.09	0.05	0.11	0.09	0.11	0.02	0.01	0.02	0.06	0.00	-0.01	-0.08	0.00	
N	1,091	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092	1,092
Mean	0.64	0.13	0.17	3.06	3.28	4.44	0.67	1.50	18.49	0.18	0.05	0.04	1.41	0.19	0.27	2009.20	6.17
Std. Dev.	0.50	0.33	0.51	3.03	3.85	2.53	0.33	1.16	9.96	0.38	0.06	0.05	2.02	0.39	0.44	2.69	3.41
Min	-0.80	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2000	1
Max	2.20	1	4	13	16	11.67	1	4.93	34	1	0.28	0.16	6.06	1	1	2012	12

3.4.4 Estimation

We estimate the following model through OLS regression

$$
\begin{aligned}
\text{Innovativeness Index}_i = & \beta_0 + \beta_1 \,\#\text{ Product Families}_i + \beta_2 \,\text{Family Length}_i + \beta_3 \,\text{Platform Age}_i \\
& + \beta_4 \,\text{Platform Concentration}_i + \gamma_1 \mathbf{X}_i + \gamma_2 \mathbf{Y}_{jt} + \varepsilon_i \qquad (8)
\end{aligned}
$$

where i indicates the focal smartphone, j denotes the manufacturer of the smartphone, t is year, and ε_i is the idiosyncratic error term for smartphone i. $\mathbf{X}_i$ contains the control variables corresponding to smartphone i (the number of smartphones launched by j in the last year, the number of platform version updates in the last year, and whether the smartphone i was launched on the manufacturer's proprietary platform). $\mathbf{Y}_{jt}$ denotes firm-year control variables (R&D intensity, number of employees, U.S. based firm dummy, and Compustat-listed firm dummy).

For estimations involving the two alternate dependent variables—dummy for boundary-advancing smartphone and the number of feature groups that advance the boundary—we use logistic and Poisson regression models to fit the above equation.

3.5 Results

3.5.1 Product Innovativeness Index

Before presenting the results of our hypotheses, it is pertinent to confirm the validity of our innovativeness index. Table 6 lists the top 20 smartphones ordered by our innovativeness index. The models from Samsung dominates the list, but other prominent manufacturers including Apple, LG, and Motorola appear as well. Our list of manufacturers corresponds strongly with public perception as well as rankings of top vendors provided by leading market research firms (Gupta et al., 2014). An examination of specific models also highlights many smartphones commonly identified for their innovativeness. Apple iPhone 4, Samsung Galaxy S2, and Samsung Galaxy S3 were awarded the best smartphone of the year in 2011, 2012, and 2013 by the Mobile

World Congress, a highly regarded industry conference for mobile technology. These three phones are indeed placed near top at 10th, 2nd, and 6th respectively in the rankings based on our proposed innovativeness index.

Table 6: Top 20 Most Innovative Smartphones

Rank	Manufacturer	Model	Innovativeness Index	Advancing Frontier?	P	D	Cp	B	Cm	Cn	S
1	Samsung	Wave	2.195	Y		Y				Y	
2	Samsung	Galaxy S II	2.150	Y	Y			Y			
3	Samsung	Omnia HD	2.092	Y					Y		
4	Samsung	Galaxy Note	1.962	Y		Y		Y			
5	Samsung	Galaxy Note II	1.910	Y		Y		Y			
6	Samsung	Galaxy S III	1.908	N							
7	Apple	iPhone	1.906	Y		Y	Y				Y
8	Huawei	Ascend D quad XL	1.868	Y		Y	Y				
9	Samsung	Omnia II	1.822	N							
10	Apple	iPhone 4	1.811	Y	Y	Y					Y
11	Motorola	A1000 Communicator	1.805	Y	Y			Y	Y		
12	Samsung	Omnia II CDMA	1.792	N							
13	LG	Optimus 2X	1.783	Y					Y		
14	LG	Optimus 4X HD	1.764	Y			Y				
15	Samsung	Beam	1.744	Y		Y			Y	Y	
16	Asus	PadFone	1.740	Y			Y			Y	
17	Motorola	Droid Razr Maxx	1.738	Y				Y			
18	LG	Optimus LTE II	1.716	Y			Y				
19	Samsung	Galaxy Nexus	1.699	N							
20	Huawei	Ascend D quad	1.699	Y		Y	Y				

Note: P-Physical, D-Display, Cp-Computing, B-Battery, Cm-Camera, Cn-Connectivity, S-Sensor

Figure 17 shows a scatter plot of all smartphone models and their innovativeness index over time. Each dot represents a smartphone model; we use color-coded symbols to differentiate between the major digital platforms (Android, Windows, iOS, Others). We note that innovativeness is increasing over time in general. iOS-based smartphones consistently rank high on the innovativeness index. iOS is a proprietary platform used exclusively on Apple products. We also see that the variation in innovativeness is greater for Android-based smartphones than for Windows-based smartphones. This can be partially explained by the fact that Android is an open-source platform that is also used in low-budget, entry-level smartphones by many different manufacturers. We also find that while Windows-based smartphones appeared as early as 2002, its innovativeness index is lower than Android and iOS counterparts in recent years.

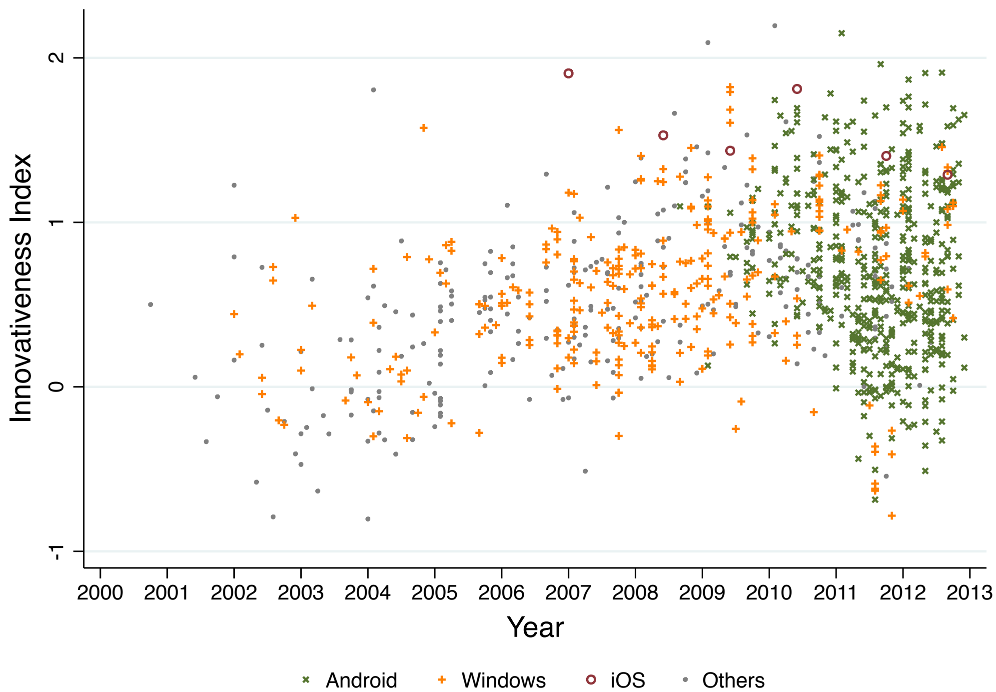


Figure 17: Innovativeness Index by Digital Platform

3.5.2 Search Strategy and Product Innovativeness

Table 7 presents the results of the OLS regression analysis. In this analysis, the innovativeness index is the dependent variable. The first column (Model 1) reports the baseline model in which the number of products, number of platform versions, proprietary platform dummy, R&D intensity, capital intensity, number of employees, U.S. based manufacturer dummy, and missing Compustat dummy were included as control variables. In Models 2-5 we introduce number of products families, product family size, platform age, and platform concentration, respectively, to assess those variables' possible effects on product innovativeness.

The number of product families concurrently offered during the previous year is positively associated with product innovativeness and statistically significant (0.048, $p < 0.01$), confirming Hypothesis 3.1. The size of the product family of a focal smartphone is also statistically significant and positively associated with product innovativeness (0.016, $p < 0.01$), supporting Hypothesis 3.2. Hypothesis 3.3 proposes that smartphones developed on older platforms tend to be less innovative. The results provide statistical support for this, with platform age negatively associated with product innovativeness (-0.022, $p < 0.05$). Finally, hypothesis 3.4 proposes that when a manufacturer concentrates its product launches on a single platform rather than distributing launches across multiple, product innovativeness will be higher. We also find statistically significant support for this, with platform concentration positively associated with product innovativeness (0.154, $p < 0.05$). In summary, all four hypotheses are supported.

In order to understand the economic significance of the results, a clear interpretation of the innovativeness index is needed. As described, the innovativeness index, in essence, denotes where on the normal curve a smartphone lies. Consider the example of a smartphone with innovativeness index equal to 1.0. As the innovativeness index is the average z-score of a new smartphone compared to prior ones, it means that our focal smartphone is one standard deviation more innovative than all previous smartphones. Put differently, the focal smartphone is superior to about five out of six existing previous smartphones following $\Phi(1) = Pr(Z \leq 1) = 0.841$, where Φ is the cumulative distribution of the standard normal distribution Z. Moreover, our results show that we have strong positive constant terms across all models. For the full model, the constant term is 0.671, suggesting that a new smartphone is technologically superior to approximately 75% of previous models. Correspondingly, we find that one unit increase in the number of concurrently developed product families in the past year is associated with a 1.5% increase ($\Phi(0.719) - \Phi(0.671) = 0.015$) in the focal smartphone's innovativeness standing. Similarly, one unit increase in product family size in the past year is associated with 0.5%p increase ($\Phi(0.687) - \Phi(0.671) = 0.005$) in the historical rank order. Each additional year to platform age is associated with a 0.7% decrease ($\Phi(0.649) - \Phi(0.671) = -0.007$). Lastly, an increase in platform concentration is associated with a 4.6% ($\Phi(0.825) - \Phi(0.671) = 0.046$) increase.

An examination of our control variables shows that the number of products released and number of platform versions used in the prior year are negatively associated with product innovativeness. However, we do not find any statistical significance for these results. Similarly, neither R&D intensity, capital intensity, nor firm size are statistically significant with product innovativeness. Our results suggest that U.S. manufacturers seems to offer slightly more innovative products, but without any statistically significant support. Smartphones developed by manufacturers that are not listed in Compustat, however, have a statistical significant negative association with product innovativeness, suggesting that more established firms are more likely to create innovative products.

We also compute variance inflation factors (VIF) to check for potential multicollinearity issues. Based on Model 5, the mean VIF is 3.00 and the highest VIF is 8.16 for platform version count. Following the rule of thumb that VIF scores greater than 10 are of concern, our results suggest that our estimates do not suffer from multicollinearity issues.

3.6 Discussion

3.6.1 Quantifying the Innovativeness of Complex Products

The new organizing logic of innovation—integrating digital platforms into physical products—requires scholars and practitioners to go beyond existing theories and practices (Yoo et al., 2010). Many of today's digitally-integrated products provide multiple functionalities. To do so, they often contain multiple different technologies. It is thus natural to view such products as complex, modular systems consisting of multiple technological subsystems. Remarkably, existing perspectives on the innovativeness of such complex products do not take into account the different parts that make up the

Table 7: Relationship between Innovativeness Index and Search Strategies

	1	2	3	4	5
# Product Families		0.046**	0.044**	0.043**	0.048**
		(0.016)	(0.015)	(0.015)	(0.015)
Product Family Size			0.015**	0.017**	0.016**
			(0.005)	(0.005)	(0.006)
Platform Age				-0.020*	-0.022*
				-0.009	(0.009)
Platform Concentration					0.154*
					(0.068)
(Log) # Products	0.038	-0.021	-0.031	-0.033	-0.043†
	(0.024)	(0.025)	(0.025)	(0.024)	(0.025)
# Platform Versions	0.001	0.000	-0.000	-0.003	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
(Dummy) Own Platform	0.004	0.042	-0.018	-0.016	-0.062
	(0.082)	(0.079)	(0.079)	(0.078)	(0.080)
R&D Intensity	0.017	-0.059	-0.312	-0.186	-0.138
	(0.577)	(0.549)	(0.537)	(0.527)	(0.519)
Capital Intensity	0.548	-0.033	0.111	0.064	0.468
	(0.521)	(0.624)	(0.553)	(0.548)	(0.565)
(Log) # Employees	-0.004	0.005	0.005	0.005	0.008
	(0.019)	(0.017)	(0.015)	(0.015)	(0.015)
(Dummy) US Manufacturer	0.019	-0.002	0.025	0.007	0.021
	(0.060)	(0.046)	(0.048)	(0.049)	(0.056)
(Dummy) Compustat Missing	-0.260**	-0.237**	-0.230**	-0.235**	-0.190*
	(0.093)	(0.082)	(0.075)	(0.075)	(0.076)
Constant	0.680**	0.655**	0.647**	0.768**	0.671**
	(0.118)	(0.112)	(0.106)	(0.127)	(0.132)
N	1,091	1,091	1,091	1,091	1,091
F-stat	5.27	13.42	15.29	19.49	18.10
Adj. R^2	0.22	0.25	0.26	0.27	0.27

Note: Year- and month-fixed effects are included in all models. Robust standard errors, clustered by manufacturer, are in parentheses. *, ** denotes statistical significance at 5% and 1%, respectively.

system, but rather focus on the innovativeness of individual technologies or components. A product that excelled in only a single technological dimension would thus be deemed innovative.

We suggest that this perspective is limiting and propose a novel way of quantifying innovativeness of complex products. We argue that all constituent technologies must be considered together to determine a product's innovativeness. Moreover, our study is motivated by the fact that, in practice, it is quite difficult and perhaps even infeasible for a product to be innovative across all technological dimensions simultaneously. There are inherent design trade-offs that must be made, both physical and logical in nature, which constrain the creation of a "best-of-all-technologies" product. Manufacturers thus make deliberate technological design choices to bring a specific smartphone to market. A multidimensional technological innovation perspective must be adopted.

In our study, we utilize all documented technological specifications to determine the innovativeness of a smartphone. We group these specifications into seven well-established and accepted performance categories. Our results show that there are clear positive evolutionary patterns within these categories and those patterns are congruent with market perception. In terms of physical characteristics, smartphones are getting thinner and lighter. All display characteristics (size, resolution, pixel density, and panel type) are improving over time. Following Moore's Law, computing characteristics (CPU, storage, and RAM) are also steadily improving. Constant improvements are also seen with battery (talk time, standby time, and capacity), camera (resolution and number), connectivity (speed and options), and sensor (number) characteristics.

In order to understand the concept of our innovativeness index, it may be helpful to draw on an analogy from sports. In the Olympics, athletes participate in the decathlon. The result in each of the ten events determines the overall performance of an athlete. Each event matters, but the success depends on the collective set. An athlete with the fastest 100-meter dash time could fail miserably in all other events. Thus, the athlete that finishes high in all events is most likely to win. We posit in our study that product innovativeness is similar. The overall innovativeness of a smartphone (i.e. performance of the athlete) is dependent on the extent of performance across all technological dimensions (i.e. performance in each Decathlon event).

Our approach thus allows us to capture a balanced view of product innovativeness and examine it in relation to the hypothetical "innovation frontier". It is flexible to future changes, as new technological features can easily be integrated. It also provides some interesting practical insights for device manufacturers. As results of top smartphones in Table 6 show, many highly innovative products do not necessarily advance the frontier. Consider the Samsung Galaxy S III, widely regarded as one of the most innovative smartphones in industry. Despite a high innovativeness index (1.908), achieved through significant computing capabilities and physical properties, the Galaxy S III did not advance the frontier. In fact, our results show that no smartphone—even a product with high innovativeness index—advances the frontier in all dimensions. On the other hand, consider the Apple iPhone 4, another award winning smartphone. On our hall-of-innovation list, it ranks 10th with an innovativeness index of 1.811. It advanced the frontier in three dimensions, including physical dimensions, display characteristics, and sensors.

These findings suggest two key things. First, for a smartphone to be deemed innovative, a device manufacturer must not necessarily advance any of the technological dimensions but rather utilize the state-of-the-art, preferably in multiple categories. This points to the broader notion that a fast-follower can reap the benefits of innovations available in the market. Second, our results show that when smartphones advance the frontier, advances tend to occur in a subset of dimensions. Figure 18 shows that physical dimensions are commonly improved in conjunction with computing and battery characteristics. Similarly, computing and display characteristics are advanced simultaneously. Device manufacturers thus should not expend their resources on trying to advance all technological aspects, but rather focus on a combination of pertinent ones.

Figure 19 shows the scatter plot of innovativeness over time for all smartphones

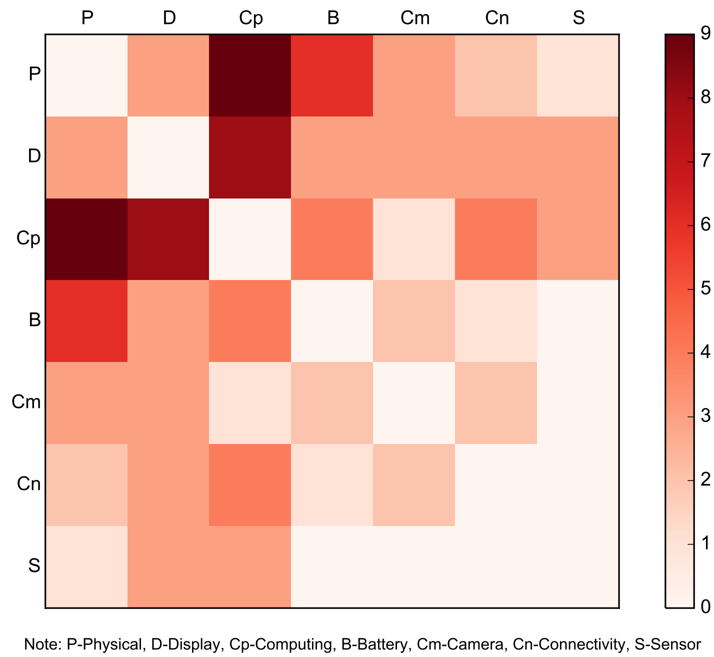


Figure 18: Co-occurrence of Advancing Frontier

and the quadratically fitted lines for two groups of smartphones. Large red dots denote smartphones that advanced the frontier at least in one feature group. Small gray dots represent product that did not advance the frontier. As expected, products with a high innovativeness index indeed advanced the frontier in many instances. However, the results reveal that there are cases where smartphones with high innovativeness index did not advance the frontier while products with low innovativeness index did. The plot also reveals that high innovativeness is generally correlated with advancing frontier in early days, while frontier-advancing and non-advancing models appear more recently.

Examining only the non-frontier advancing products (gray dots), we also can observe that the average innovativeness increased until 2010 and then suddenly diverged afterwards. In contrast, the average innovativeness of frontier-advancing smartphones has consistently increased over the study time period. It confirms how robustly the innovativeness index captures the overall innovation landscape of the industry compared

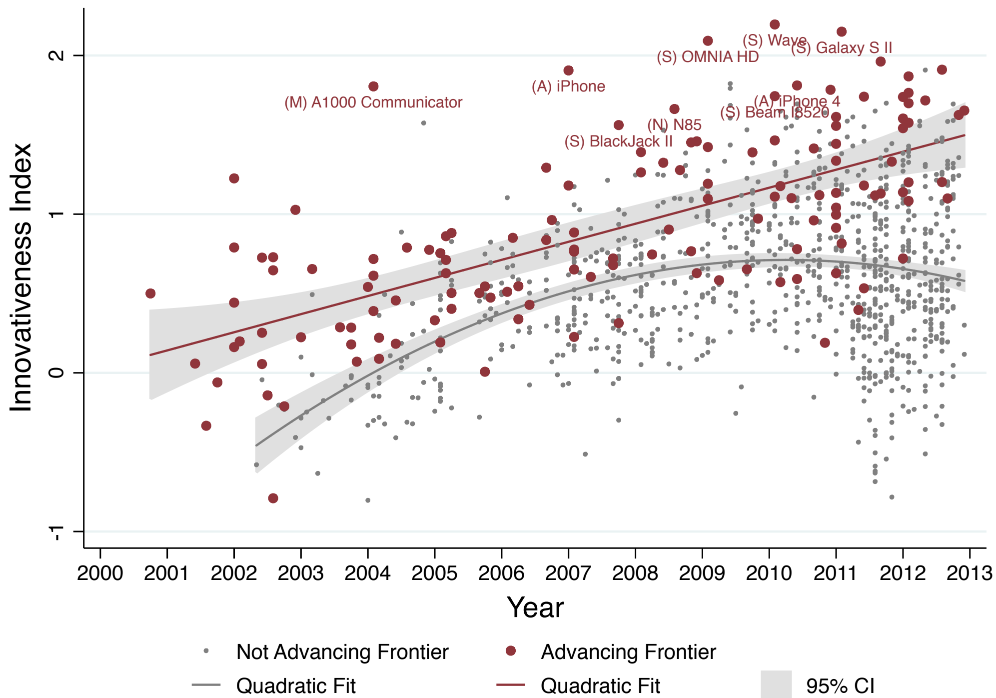


Figure 19: Depiction of the Innovation Frontier

to the raw evolution charts of individual technological features in Figure 15. While many computing-related individual technical features exhibit exponential growth over time following the Moore's Law, the innovativeness index grows in linear scale and is contained within a sensible bound. This stabilization comes from the fact that we define innovativeness relative to prior products. This is indeed natural way of thinking about innovativeness; top products keep surpassing their predecessors, but the market is eventually flooded by mediocre phones.

3.6.2 Managing Product Families and Digital Platforms

In a multidimensional technology landscape, firms make deliberate innovation search strategy choices in order to avoid potentially undesirable or costly outcomes. Prior work has suggested benefits of diverse search strategy approaches, including local versus distant search, depth and breadth search, and even sequential versus parallel search. As physical products are increasingly digitized and the role of software increases, hardware–software combinations need to be explicitly studied in product innovation research. In this study, we frame two hardware–software product innovation phenomena as concepts in search space, namely product families and digital platforms.

The use and extension of a product family can be thought of as search depth strategy; the use of multiple product families can be thought of as parallel search. While not entirely new, prior work has not explicitly conceptualized product families as an explicit search strategy. The integration of digital platforms into physical products on the other hand is relatively novel and has not been addressed in the innovation search literature to date. We conceptualize digital platforms as boundaries in search space, enabling and highlighting possible search areas.

In an increasingly competitive business environment, device manufacturers continuously seek to find ways to create innovative new products. Our study shows that choosing appropriate product family and digital platform strategies can help with this pursuit. With respect to product families, device manufacturers must decide on how many different product families to offer and whether to extend a product family. We theorize, in Hypothesis 3.1, that multiple product families allow a manufacturer to cover a larger area of the search space, resulting in a greater probability of creating breakthrough innovations. We conceptualize product family to be a specific search path through search space. Our thinking thus builds on the recognized benefits that parallel search processes allow firms to explore the search space more broadly and effectively. Our results confirm that device manufacturers can create more innovative products with more product families. It enables manufacturers to gain broader knowledge of viable areas of the search space, allowing them to discard poor technology choices and integrating good results into future offerings.

Extending product families, as theorized in Hypothesis 3.2, also falls into the line of thinking that firms can reap benefits through organizational learning. The longer and deeper the search path, the greater the probability of producing innovative outcomes. Our study shows that manufacturers can and in fact should build on the knowledge they have accumulated over time. By extending product families, the next search step is more incremental, allowing a manufacturer to exploit an area in which it has already built expertise. Our results suggest that product innovativeness is thus a function of product family extension and parallel search.

The consideration of digital platforms as an integral part of their physical product offering is a relatively new phenomena for device manufacturers. Given the prominence of digital platforms, however, manufacturers have to make some important platform strategy decisions. Broadly, manufacturers must contemplate two decisions: which platform(s) to adopt and, if multiple, which one to focus on as their primary platform. A more complex decision for manufacturers is to whether to offer their own proprietary platform.

Hypothesis 3.3 states that firms have to continuously search and seek out new sets of potential combinations in order to stay innovative. Our results show that regions of the search space have an expiration date. The older the search region is, the less likely a device manufacturer will innovate. This idea is in line with prior thinking that firms can eventually exhaust a search space. Firms try all incremental or new recombinations, and eventually no new ones are available. Our theory suggests that new platforms enable new regions in search space, allowing for novel recombination of features. Our results indeed confirm that platform age has a negative impact on product innovativeness. This finding suggests that device manufacturer should, if possible, seek out newer platforms.

Of course, this comes at a trade-off. While new platforms offer new opportunities to innovate, firms must allocate potentially significant resources and capabilities to "re-tool" and explore a possibly new search area. So, what platform portfolio strategy should a manufacturer pursue? We theorized, in Hypothesis 3.4, that a concentrated platform strategy leads to higher product innovativeness. Indeed, our results confirm that device manufacturers that have adopted multiple platforms, but focus on one, tend to create more innovative products. The implications are multifold. The results suggest that firms pursuing multiple platforms learn and accumulate new knowledge about the search space. However, they should not distribute their efforts on each platform evenly. Once they find a reasonable region in search space, they should start focusing on that single region. This result is in line with the resource-based view of firms that only a limited number of activities (e.g., pursuing platforms) can be supported simultaneously.

The results also have practical significance. Firms should continuously learn but eventually focus their efforts on one platform. In an era where there is an increase in platform competition and new platforms emerge regularly, firms must make difficult choices in abandoning the "platform" ship, staying with single platform, or joining multiple platforms. Our results demonstrate that a multiple platform strategy is indeed beneficial, however we provide a more fine-grained differentiation between that of a multiple platform and multiple-concentrated platform strategy.

3.6.3 Advancing the Innovation Frontier

The discussion so far has focused on overall product innovativeness. However, as we noted earlier there are also two alternative perspectives of innovation as well, namely whether a smartphone has advanced a boundary and the total number of boundaries advanced. We use Logistic and Poisson regression models respectively to estimate Equation (2).

Table 8 shows the results of our post-hoc analysis. We only include the full model specification. Columns 1-2 show the raw estimates; columns 3-4 report marginal semi-elasticity, $\frac{dy}{d(\ln x)}$. When the independent or control variable is in logarithmic form, we report raw marginal effects, $\frac{dy}{dx}$.

Table 8: Relationship between Frontier-Advancing Innovation and Search Strategies

	Raw Coefficient		Semi-elasticity	
	1 (Dummy) Boundary Advanced	2 # Boundaries Advanced	3 (Dummy) Boundary Advanced	4 # Boundaries Advanced
# Product Families	0.139**	0.131**	0.038**	0.058**
	(0.045)	(0.033)	(0.013)	(0.015)
Family Length	0.015	0.011	0.005	0.005
	(0.029)	(0.026)	(0.009)	(0.013)
Platform Age	-0.117*	-0.108*	-0.044*	-0.062*
	-0.055	(0.049)	-0.019	(0.027)
Platform Concentration	0.805†	0.619†	0.049	0.063†
	(0.475)	(0.322)	(0.031)	(0.037)
(Log) # Products	-0.264	-0.243†	-0.024	-0.042†
	(0.173)	(0.133)	(0.016)	(0.023)
# Platform Versions	-0.022	-0.015	-0.033	-0.034
	(0.015)	(0.015)	(0.022)	(0.034)
(Dummy) Own Platform	-0.766*	-0.372	-0.015**	-0.015*
	(0.316)	(0.242)	(0.005)	(0.008)
R&D Intensity	5.127	3.534	0.030	0.040
	(3.145)	(2.253)	(0.019)	(0.025)
Capital Intensity	8.102**	7.809**	0.033**	0.066**
	(2.576)	(2.274)	(0.010)	(0.021)
(Log) # Employees	0.150*	0.111**	0.014*	0.019**
	(0.064)	(0.041)	(0.006)	(0.007)
(Dummy) US Manufacturer	-0.351	-0.226	-0.006	-0.008
	(0.284)	(0.234)	(0.004)	(0.007)
(Dummy) Compustat Missing	0.576	0.421	0.010	0.012
	(0.516)	(0.377)	(0.011)	(0.013)
Constant	-1.994**	0.700†	N/A	N/A
	(0.738)	(0.409)		
N	1,087	1,092		
Log pseudolikelihood	-344.41	-455.82		
Wald χ^2	1577.20	9257.30		

Note: Models 3-4 report semi-elasticity marginal effect, $dy/d(\ln x)$. Model 1 and 3 are estimated by logistic regression model; Model 2 and 4 by Poisson regression model. Year- and month-fixed effects are included in all models. Robust standard errors, clustered by manufacturer, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

We observe several interesting differences from our original innovativeness index analysis. Only the number of products and platform age are moderately significant; platform concentration is marginally significant in the Poisson regression. As these two variables conceptualize search scope—number of search paths (from a product family perspective) and activated region (from a digital platform perspective)—we can derive that advancing the innovation frontier is primarily associated with enlarging search scope. It may also imply that knowledge spillovers across different regions of the search space are of greater importance when advancing the innovation frontier.

There are also interesting and significant changes in the control variables. Both capital intensity and firm size (as measured by number of employees) strongly explain the probability and propensity of boundary-advancing smartphones. In contrast, R&D intensity is quite insignificant, suggesting that defining the innovation boundary is an endeavor of capital and size rather than R&D.

3.6.4 Practical Implications

The innovation index developed and proposed in this chapter provides a way to quantify the innovation landscape for a product market. Product managers in manufacturer companies may be able to leverage our approach and measures used in this chapter to develop their own business intelligence systems that can assist strategic product positioning planning. Table 6 previously showed the list of the top smartphones in the history of the industry. It showed which smartphones were good products overall and which pushed the innovation frontier of the industry. This type of analysis can be narrowed down and performed within a company instead of the entire industry in order to help individual companies plan and position their new products.

Moreover, this chapter is particularly relevant to the product companies that have close relationships with digital platforms. Although digital platforms have played an important role in some consumer electronics product categories so far, their role will be increasingly prominent for traditionally considered as brick-and-mortar product and business categories as well. For example, automobiles are more and more powered by digital platforms. Our study can inform product managers at those companies influenced by digital platforms. Choosing a platform for new products, product managers need to consider the obsoleteness of the platform and balance among multiple platforms. The platform is an inherently constraining factor for new configurations in the product development space, so choosing it with deliberate effort may save unnecessary costs down the road.

One of the unexpected results is the differential impact of product family management and platform strategy on the innovation index and the probability of pushing the innovation frontier. Overall goodness of products represented as the innovation index is influenced by both search scope and search depth in product family and platform choice. However, pushing the innovation frontier of the industry is only associated with search scope. Developing a new product that surpasses existing products in any technical dimension requires exploratory activities of the search space. This nuanced finding is new to our previous knowledge on new product development.

3.7 Conclusions

In this chapter, we propose and develop a novel innovativeness index for complex multi-technology products. We then theorize and empirically test the relationship between product family and digital platform strategy on product innovativeness in the highly dynamic smartphone industry using a unique dataset from 2000-2012. Specifically, we extend current theories of innovation search by conceptualizing product family and digital platforms as paths and regions in search space.

We find that concurrent number of product families and size of the focal product family are positively associated with product innovativeness. These results corroborate findings from prior work on search breadth and depth, respectively. Our results also suggest that products developed on older digital platforms are less innovative, confirming that platforms activate search regions and search spaces can be exhausted. Lastly, we find that a concentrated digital platform strategy, in which manufacturers pursue multiple, but focus their efforts on a single digital platform, has particularly positive outcomes on product innovativeness. This finding is supported by principles of organizational learning and resource-based view of firms.

Our study contributes to product innovation theory and practice at the intersection of operations management, information systems, and strategy. Specifically, we empirically demonstrate how the new modular, layered product architecture—fusing the physical and logical layers—influences product innovativeness. We hope that our study, and the concepts developed in it, forms the basis for future innovation research of complex products in an increasingly digitized world.

Our study is not without limitations. First, we focus our analysis on a single product domain. Unquestionably, the smartphone industry is one of the early domains where software and hardware are inextricably intertwined. Future research should examine how our theory holds up in related product categories, such as tablet computers, or other emerging platform domains, such as video games, medical devices, or electric vehicles. Second, we acknowledge that platforms are continuously updated and improved. Although we control for the number of version updates released by the platform provider in our analyses, future research should examine the role of version upgrade types such as major, minor, and patch updates on product innovativeness. Lastly, an interesting extension of our study would also include an examination of other ecosystem stakeholders and their contributions to innovativeness. It is well recognized that third-party application developers are playing an influential role in the broader mobile ecosystem and that smartphones are merely a vehicle to value creation and delivery. With increasing importance of software applications, an investigation how product innovativeness enables and fosters new types of applications/developers and how the need of new types of applications drive the direction of product innovation would be an exciting direction for future research.

CHAPTER IV

PRODUCT INNOVATION AND EXCLUSIVE PARTNERSHIP WITH SERVICE PROVIDERS

4.1 Introduction

The previous chapter develops a theory of the innovation process for new product development in a search space constrained by digital platforms. We empirically validate the proposed search space theory in the smartphone industry using a newly developed measure for product innovativeness. This chapter looks at another integral relationship in the triadic industry structure: the relationship between manufacturers and network service providers. This relationship is similar to that between manufacturers and platform developers in that the two parties are codependent for developing and launching a new product. A smartphone, before anything else, is a mobile phone that requires connection to the cellular network operated by a network service provider. One key difference is that service providers do not have such a strong grip that platform developers have in order to influence the technical specifications of the products. Yet, we find that service providers can leverage their consumer base to regulate the level of competition on the manufacturer side and affect the technical evolution of products in a rather implicit way. In particular, this chapter pays close attention to how the service provider's selection of products to be available on its network influences manufacturer-side competition and the evolution path of product technical specifications over time.

Procuring high-quality products from high-profile suppliers is one of the most important success factors for distributor or retail businesses facing consumers (Weigelt, 2013). Even better, if an exclusive arrangement can be made, the partnership can become a source of competitive advantage from differentiation (Subramanian et al., 2013). Stories of retailers and platforms pursuing premium suppliers in real business practices are plentiful. In 2012, Starbucks Corporation acquired a San Francisco-based boutique bakery, La Boulange, after looking for a way to improve the quality of its pastry lineup. In the digital world, video game consoles sometimes have exclusive game titles available only on their own platforms. A series of franchise star titles such as Halo on Microsoft Xbox helped retain existing customers and even induced switching or multihoming from the user base of the competing consoles.

As much as looking for premium suppliers, downstream distributors also have an incentive to regulate quality of supplier products. They set up explicit acceptance criteria that eventually influence the evolution trajectory of product design due to strategic reaction of suppliers (Luo et al., 2007; Williams et al., 2008). Implicit factors like distributor market structure also influence the product design evolution (Williams et al., 2011). However, the existing literature on strategic product design has focused on the relationship between manufacturer and retailer, leaving the competitive aspects among manufacturers largely unexplored. In this chapter, we examine how distributors can introduce a disruptive product in their network to intensify supply-side competition so that suppliers need to provide their technologically superior products to them. As a result, a distributor's product assortment choice implicitly shapes the technology evolution trajectory without explicit guidelines on product specifications.

In 2007, the U.S. telecommunications industry witnessed the arrival of a new smartphone, which transformed the industry permanently. The introduction of the Apple iPhone was a game changer for the whole mobile ecosystem affecting all types of players operating in the industry: handset hardware manufacturers, network carriers as cellular service providers, software companies, and application development communities (Basole, 2009). Before the iPhone, network carriers had governed and led the ecosystem as they could force manufacturers to ship some of their own software and dictate which software programs would run on the device. They were even able to influence the hardware specifications of the handset, but they lost their strong grip on hardware after the iPhone (Vogelstein, 2008).

The iPhone changed not only the way the industry works from a platform and software perspective but also from a hardware product innovation perspective. While it did not necessarily have the best technological aspects, it offered a balanced combination of existing technologies. In this sense, the iPhone can be regarded as a prime example of architectural innovation that successfully recombined existing core components in a novel way (Henderson and Clark, 1990). Still, some of its hardware components were in fact state of the art (e.g., built-in exotic sensors such as accelerometer, large capacitive touch screen, spacious permanent storage). What makes this setting particularly fitting for our study is that the iPhone was released exclusively on the service carrier network (AT&T). This exclusivity continued for nearly four years until a successor model of the original iPhone was finally released on a competitor service network (Verizon).

From AT&T's perspective, the adoption of the iPhone exclusively on its network was a risky bet (Mehta, 2007; Sharma et al., 2007). The strategic upside was to boost market share by inducing consumers fond of the iPhone to switch from competitors and tying those consumers to the usual two-year contract. On the contrary, the downside would be that the whole wireless carrier business could be commoditized and marginalized by yielding profitable revenue sources to the platform developer providing more flexible and transparent service (Vogelstein, 2008). For instance, the short messaging service, one of the most lucrative services for network carriers, became almost completely obsolete due to apps that provide free messaging service using the Internet (West and Mace, 2010). In retrospect, the deal turned out to be mutually successful for both Apple and AT&T.

Exploiting this temporal asymmetry in adoption timing, we study how hardware suppliers react to the debut of a potentially disrupting product by adjusting the product design and deployment decisions. We compare phones supplied to AT&T with those to Verizon or other network carriers before, during, and after the exclusive contract. We quantify the overall goodness of a phone relative to phones preexisting in the market beforehand. Using the proposed measure, we estimate the average treatment effect using the difference-in-differences (DID) method. We find that manufacturers first avoid competition by clinging on to old product categories and reducing smartphones in their product mix. However, they eventually recognize the transformed product competition landscape and pursue head-to-head competition. Moreover, in response to the disruptive product, competing manufacturers supplied their technologically superior products to AT&T over the exclusive contract period. For a given manufacturer, products supplied to AT&T were better than those supplied to other network carriers by 0.239 standard deviation. The manufacturers particularly focused on product features—display, computing, and sensors technology—in which the iPhone excelled. This asymmetric competition-induced product enhancement decision of manufacturers persisted even after the exclusive contract had expired. Our study builds on the extant literature on strategic product design for channels and contributes to the understanding on strategic implications of disruptive technology adoption (Gaimon, 2008).

The rest of the chapter unfolds as follows. Section 4.2 reviews theoretical background and develops hypotheses. Section 4.3 describes our data sources and empirical identification strategy. Section 4.4 reports our main results testing the hypotheses. Section 4.5 provides robustness checks and discusses firm-level implications of our findings and Section 4.6 concludes the chapter.

4.2 Theoretical Background

From a new product development perspective, the literature on strategic product design for distribution channels provides the theoretical foundation for this chapter. Luo et al. (2007) and Williams et al. (2008) studied the interaction between suppliers and distributors on the product level by showing how the distributors' product acceptance criteria influences the suppliers' new product design. Williams et al. (2011) further examined how distributor-side market structure influences new product design. Our study complements this research stream by highlighting the endogenous competitive aspects in the interaction between suppliers and distributors in the presence of disruptive innovation. Observing longitudinal responses allows us to differentiate between short-term and long-term reactions, which sheds light on the dynamic product evolution trajectory.

Our research also touches on the exclusive dealing literature. Since access to and acquisition of quality suppliers can be a source of competitive advantage as it allows differentiation, exclusive dealing has been studied extensively in many academic fields including applied microeconomics, supply chain, and marketing. Marvel (1982) and Aghion and Bolton (1987) established the definition of exclusive dealing and the conditions when such an exclusive arrangement arises. Many theoretical (e.g., Besanko and Perry, 1993, 1994; Fumagalli and Motta, 2006) and empirical (e.g., Sass, 2005) studies have followed. These microeconomic setups have influenced contemporary supply chain studies (Shou et al., 2009; Chen and Guo, 2013; Wang and Shin, 2014).

In terms of research setting, our study connects to a line of research motivated by the success of the iPhone. Because of exclusive launches in many countries (Cho et al., 2014), the iPhone triggered several legal and economic analyses about tying, contract restrictions, and antitrust issues. These legal cases corroborate the significant market impact of the iPhone. Naturally, many academic studies have paid attention to the exclusive arrangement made between Apple and AT&T for the iPhone (Chen and Riordan, 2007; Bougette et al., 2012). The marketing literature, in particular, has made a series of attempts to model the exclusive contractual structure. Most of them are theoretical modeling pieces employing a game-theoretical approach. Subramanian et al. (2013) provide competitive analysis caused by exclusive arrangement, while Sinkinson (2011) analyzes entry incentive upon exclusive contract. Both of them specifically pinned their context to the smartphone industry. Cai et al. (2012) generalized the problem to operating exclusive channels and revenue sharing. Despite the impact of this exclusive arrangement, surprisingly, only a few studies performed empirical investigation on the iPhone's exclusive launch. Zhu et al. (2011) have shown the changes and prediction of market share among major network carriers adjusting price effect. Cho et al. (2014) looked at how exclusive contract affected consumer demand across six different countries. To the best of our knowledge, no studies have investigated product-level action-reaction triggered by the exclusive contract of the iPhone.

4.2.1 Hypotheses Development

The first competitive response we hypothesize is the adjustment of product assortment from the manufacturer's perspective. Manufacturers have incentive to both increase and decrease the portion of the "disrupted" product category among those supplied to the "disrupted" distributor that adopted disruptive product. The direction seems ambiguous in the lump sum, so we need to delve into the logic for each direction and decompose the incentive temporally. The pressure for decreasing the disrupted product category in product mix is from the competition in the supply side as the disruptive product will raise consumers' expectations for the disrupted product category. At first, competitors may not realize that the new product is disruptive or not until the market has turned over (Christensen, 2013). We can expect that competing manufacturers simply focus on old product categories just to avoid competition in the short run.

The opposite pressure for increasing the disrupted product category in product mix comes from the consumer demand side as consumers with strong desire for the disruptive product self-select to subscribe to the disrupted distributor. In the long run, the disrupted distributor may arise as an icon for the disruptive product and the competing manufacturers will eventually accept the disruption as reality. They will readjust the product assortment with emphasis on the lineups in the disrupted product category. This rebound in product mix will be primarily associated with the disrupted distributor because of the preferential attachment mechanism (Venkatraman and Lee, 2004). In the long run, competing manufacturers will try to mute down the disruptive product by flooding the disrupted distributor's network.

Hypothesis 4.1a *In the short run, manufacturers decrease the proportion of the disrupted product category in their product mix.*

Hypothesis 4.1b *In the long run, manufacturers increase the proportion of the disrupted product category in their product mix particularly for the disrupted distributor.*

Moving from product mix to technical details of products, we can reasonably expect that manufacturers will attempt to enhance technical specifications for the products supplied to the disrupted distributor compared to those supplied to other channels. This mechanism has been studied in the competitive dynamics literature as the Red Queen effect. One firm's strategic competitive action triggers rivals' reactions that erode the impact of the original action. Firms are running as fast as they can just to stay at status quo and they need to run twice as faster than others to stay ahead (Derfus et al., 2008). The novelty in our theoretical formulation lies on the conjecture that firms in one industry can leverage from the partnering industry's intensified Red Queen competition to create a sustainable competitive advantage. Firms are not mere subjects in the Alice world, but they can adjust the pace of competitive reactions in the adjacent industry.

One possible account of this competition-induced product enhancement hypothesis comes from the market expectation perspective. When a disruptive technology becomes available through the disrupted distributor, consumers are exposed to the new value proposition brought by the new product. Some consumers in competing channels may even migrate to the disrupted distributor because of this new product if multihoming is limited. Johnson et al. (1995) suggests that consumers facing a disruptive market change caused by a new product adjust their expectations on product performance for other products. Thus, consumers subscribing to the disrupted distributor would have significantly higher expectation on the overall product performance. Another explanation is that subscribers to the disrupted distributor have a larger choice set simply because one new product is added. Evidently, being chosen from a larger choice set is harder than from a smaller set unless the disruptive product is a mediocre choice item in the set. In sum, the disrupted distributor becomes a tougher contest stage for the disrupted product category due to the raised expectation of the consumers in the network. Facing this change on the demand side, manufacturers supplying products to both disrupted and undisrupted distributors are expected to keep up with the rising consumer expectations (Bridges et al., 1995). In order to stay attractive in the disrupted distributor's network, the competing manufacturers need to supply technologically superior products. Moreover, as followers to a disruptive product, manufacturers will engage in mimicry and particularly focus on the technology areas that the disruptive product excelled in.

Hypothesis 4.2a *Manufacturers provide one's better products to the disrupted distributor.*

Hypothesis 4.2b *Manufacturers particularly improve the product technical specifications that the disruptive product excels in.*

Exclusive arrangements may or may not be permanent. If exclusivity is achieved in the form of vertical integration or acquisition, such exclusivity may deem perpetual. If two parties cooperate on a common goal only for the time being, such an exclusive contract is likely in a limited term. If exclusive dealing is a key mechanism to intensify competition in other partnering industries, it is a valid question to ask whether the positive effect hypothesized by H4.2a will be canceled out or even turn negative when the exclusive contract ends.

When an industry—as collective organization—reaches an equilibrium state, it resists to change due to industry inertia (Bozzo, 2002; White and Yanamandram, 2004). To keep inertia as a defensive barrier, industry leaders often run retention programs to maintain customer loyalty. Customers purchasing a product or subscribing to a service may also develop a sense of community among themselves, which serves as an industry inertia that resists to change from the status quo (Fraering and Minor, 2006). In our context, such industry inertia can be expected to exist both on the manufacturer and on the subscriber side. On the manufacturer side, the equilibrium is that no single manufacturer will have a unilateral incentive to lower back the technical specification for products supplied to the disrupted distributor even when the exclusive contract for the disruptive product ends. On the subscriber side, customers will maintain the perception that the disrupted distributor deals superior products than other service providers. Given these sources of industry inertia, we expect that a manufacturer's supply behavior change caused by an exclusive contract will persist even if the contract ends. That is, once the disrupted distributor starts attracting better products relative to other carriers, this new equilibrium will not be undone just by ending the exclusive contract. We refer to this persistence over time as temporal competitive spillover.

Suppose it turns out that the disrupted distributor indeed sources better products in the disrupted product category affirming H4.2a. The main driver for such behavioral change of manufacturers is rising consumer expectation. This also suggests that tech-savvy customers self-select to migrate to the disrupted distributor network, which makes the disrupted distributor customer base more sensitive to the technological superiority of the product on the network. With this new customer base, and due to the umbrella branding effect, the disrupted distributor may be perceived as a network carrier that runs technologically superior products on its network not only for the disrupted product category but also adjacent old product categories. We can then expect that even consumers who are late in technology adoption, if their preferences are more sensitive to technology itself, will switch to the disrupted distributor from other distributors. Assuming that manufacturers react in the same way to such a change in customer composition, we can formulate a hypothesis describing the horizontal (i.e., product categorical) competitive spillover effect.

Hypothesis 4.3a *Manufacturers provide one's better products to the disrupted distributor even after the exclusive contract for the disruptive product ends.*

Hypothesis 4.3b *Manufacturers provide one's better products to the disrupted distributor not only for the disrupted product category but also for adjacent old product categories.*

4.3 Data and Methods

4.3.1 Data Source

Our data come from PhoneArena.com, which is a web service that collects technical specifications of mobile handsets. It is a comparable source to GSMArena.com, which has been used by several prior research published in academic outlets. Each handset device is categorized as one of four types: basic phone, feature phone, smartphone, and tablet. We excluded tablet because tablet has different value proposition and consequently different user base. Tablet also differs from phone in a sense that access to cellular network is not essential for its value proposition. Our primary focus in our study is mobile phone. When phone type is blank, we categorized them as basic phone. We also grouped basic phone and feature phone together because smartphone is the product category disrupted by the arrival of the iPhone. We also removed cases when the phone was canceled not released to the market eventually. Lastly, we manually merged duplicate entries primarily based on manufacturer, device type, announced date, and physical dimensions. Two same type phones from the same manufacturer announced on the same date having exactly the same length, width, weight are regarded the same products. Final merge was done by hand to ensure different phones remain as separate entities. In a few cases, some distinct phones from the same manufacturer indeed do share the same dimensions and announced date. Finally, this initial screening and classification results in 4,386 phone entries.

Each entry also contains information about manufacturer and carrier, announced date, and detailed technical specifications. The technical specifications of each record include physical properties (dimensions and weight), display quality (e.g., panel size, pixel density, and panel type), computing power (e.g., CPU clock speed and number of cores), battery performance (e.g., capacity and talk-time), camera quality (e.g., number of pixels, availability of secondary camera, and movie quality), connectivity standards (e.g., cellular network speed and supported Wi-Fi standard), and number of built-in sensors (e.g., gyroscope, and proximity sensor).

4.3.2 Sample and Variable Construction

Our initial sample contains 4,386 phones and their various technical specifications from PhoneArena.com. For the description of the data source in full details, refer to Chapter 3. The main focus of this study is to examine the changes in products' technical characteristics in the advent of the iPhone. If we tested for each technical characteristic, the analysis would be inefficient and hard to summarize generally. Thus, we need a variable that summarizes the technological superiority of a handset in a quantifiable way. Similar to Chapter 3, we grouped detailed technical specifications into seven technical property groups as briefly introduced in the previous section. Each group contains different number of subdimensions (or technical properties). For instance, the physical dimension contains two subdimensions: thickness and weight. The characteristic of each subdimension is converted into standardized z-score. To compute the z-scores, we need a benchmark set of products that serves as a underlying distribution to which focal technical property is compared. We define all previous phones of the same type announced before the focal phone as the benchmark set. That is, every phone is compared against all previously announced phones. When computing z-scores, we transformed some technical properties into logarithmic scale if the property is highly skewed. Such technical properties include CPU clock speed, network speed, and camera quality (number of pixels). The computed z-scores in each technical subdimensions are then averaged within each major group. Finally, the average z-score across the seven major groups becomes the product innovation index of the focal phone. The innovation index was computed separately between basic phone and smartphone. Equation (9) summarizes how the innovation index was computed for each phone.

$$\text{Innovation Index}_i = \left(\sum_{c \in C} \left(\sum_{x \in c} \frac{x_i - \mu_x(t)}{\sigma_x(t)} \right) / |c| \right) / |C| \tag{9}$$

where $C = \{\text{Physical, Display, Computing, Battery, Camera, Connectivity, Sensor}\}$ and $|C| = 7$. Each $c \in C$ denotes the set of subdimensions belonging to each technical property group and $|c|$ is also size of set c. Each $x \in c$ denotes specific technical property such as thickness in the physical properties. $\mu_x(t)$ and $\sigma_x(t)$ are mean and standard deviation of x of all phones in the benchmark set launched before time t. In essence, the innovation index of phone i is average of averages of standardized z-scores of technical properties. It implies equal weights among subdimensions in the same group and equal weights among seven technical property groups. For detail tech spec classifications, refer to Chapter 3.

Once we compute the innovation index based on the aforementioned 4,386 data points, we further narrow down the sample to elicit our empirical setting. We first funnel the sample by keeping only manufacturers that have announced phones both before and after the announcement of the iPhone. Since our focus in this study is to compare before and after the behavior of competing manufacturers of Apple, such manufacturers must have existed and offered phones before and after iPhone. Apple products were also removed from the dataset as we view the release of the iPhone as an exogenous event to the industry and our goal in this chapter is to observe other manufacturers' reactions to the action. 3,011 phones from 26 manufacturers remained after applying this first criterion. Next, we surveyed the list of products launched by each manufacturer. We looked at which carriers those products were launched. Since the marking of carrier information is important in our empirical setting, we removed manufacturers whose products have not been associated with any U.S. network carriers. We also removed manufacturers who have not launched any products on the AT&T's network because phones launched on the AT&T's network is the treatment group and those on other carriers' network become control groups. Finally, we removed phones that do not have the corresponding innovation index. The final dataset for the main analysis contains 2,691 observations including 1,914 basic phones and 777 smartphones spanning from 1999 to 2013. The dataset ends on June 30, 2013. The dataset contains 13 manufacturers. Top manufacturers by the number of launched phones are Samsung (874 phones), LG (452 phones), Motorola (376 phones), and Nokia (368 phones).

Figure 20 shows the distribution of the innovation index, our main dependent variable, over the phone categories. Histogram shows innovation index of all phones and kernel density plots show the index of basic phone and smartphone. First of all, we confirm that innovation index defined by Equation (9) closely resembles the normal distribution. The normality of the main dependent variable is a desirable characteristic for OLS regressions. Next, we see that the mean of the distribution is above zero, which confirms the obvious intuition that technical properties have improved over time. Lastly, the mean innovation index of smartphone is greater than that of basic phone. That is, the technical leap between a new smartphone and its benchmark of previous smartphones is larger than that between a new basic phone and its benchmark of previous basic phones. In other words, smartphone as a product category has improved in technical specifications more drastically than basic phone.

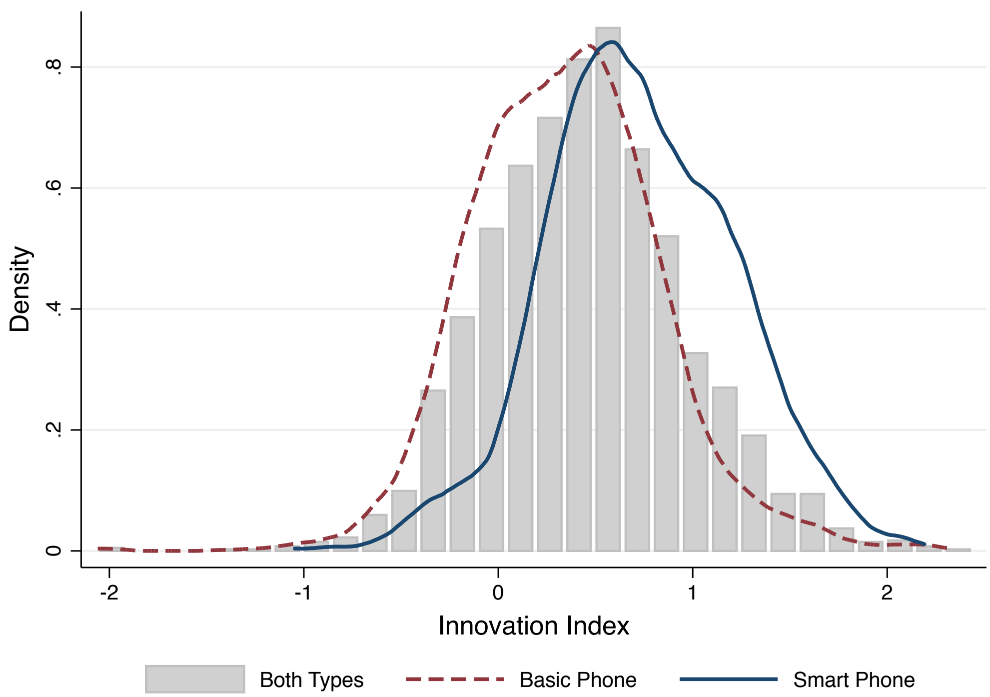


Figure 20: Product Innovativeness Distribution Over Phone Types

Table 9 shows the summary statistics and correlations of the main variables. Many of our variables are dummy variables denoting time and carrier. The period during which Apple and AT&T had an exclusivity agreement on iPhone was defined from January 9, 2007 to January 11, 2011 when iPhone 4 was released on the Verizon's network (Figure 21). Two dummy variables denoting the times during or after the exclusive contract are defined in Equation (10) as follows.

$$\begin{aligned} \text{During}_i &= 1 \text{ if } t_i \in [\text{01-09-2007}, \text{01-11-2011}) \text{ otherwise } 0 \\ \text{After}_i &= 1 \text{ if } t_i \in [\text{01-11-2011}, \text{06-30-2013}] \text{ otherwise } 0 \end{aligned} \tag{10}$$

Three carriers (AT&T, Verizon, and T-Mobile) are denoted by separate dummy variables. From the raw pairwise correlation shown in Table 9, we can make rough observations on the trends of product innovativeness in the mobile handset domain. First, smartphones are technically superior to basic phones as being a smartphone is positively correlated with higher innovation index. Second, innovation index has grown over time as seen in the positive correlation with year or during and after dummies. Lastly, Verizon seems to carry more innovative products in general. Note that these comparisons are based on raw pairwise correlation, so it only tells the pairwise relationship between two variables without controlling for other compounding effects, which will be the main results of this chapter.

Table 9: Summary Statistics and Pairwise Correlations

Variable	N	Mean	Std. Dev.	Min	Max	Pairwise Correlations							
Innovativeness	2,691	0.46	0.51	-2.06	2.31								
(Dummy) Smartphone	2,691	0.29	0.45	0	1	0.34							
(Dummy) During Exclusive Contract	2,691	0.47	0.50	0	1	0.10	-0.08						
(Dummy) After Exclusive Contract	2,691	0.19	0.39	0	1	0.14	0.34	-0.46					
(Dummy) AT&T	2,691	0.14	0.34	0	1	0.04	0.07	-0.08	-0.02				
(Dummy) Verizon	2,691	0.11	0.31	0	1	0.18	0.06	-0.05	0.00	-0.08			
(Dummy) T-Mobile	2,691	0.07	0.26	0	1	-0.01	0.06	-0.04	-0.02	0.12	-0.04		
Year	2,691	2007.70	2.95	1999	2013	0.28	0.32	0.26	0.65	-0.10	-0.05	-0.06	
Month	2,691	6.16	3.52	1	12	-0.01	-0.02	0.04	-0.07	0.02	0.01	0.04	-0.06

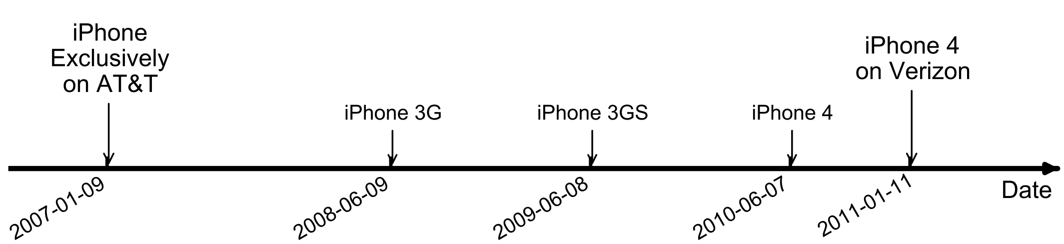


Figure 21: Timeline of iPhone Announcements on AT&T and Verizon

4.3.3 Estimation

Harnessing the contrast between AT&T and other carriers triggered by the exclusive contract of the iPhone, we use the DID method to estimate the impact of exclusive release of iPhone on the competitive landscape of product design and innovation. Although we tease out other major carriers in the U.S.—Verizon and T-Mobile—in some models, our baseline estimation model is as follows in Equation (11).

$$\begin{aligned}\text{Innovation Index}_i = &\alpha + \beta_j \text{AT\&T} + \beta_{t1}\text{During Exclusivity} + \beta_{j,t1}\text{AT\&T} \times \text{During} \\ &+ \beta_{t2}\text{After Exclusivity} + \beta_{j,t2}\text{AT\&T} \times \text{After} + \gamma_k + \gamma_y + \gamma_m + \varepsilon_i\end{aligned} \tag{11}$$

where j and k denote carrier and manufacturer of phone i. $\gamma_k, \gamma_y, \gamma_m$ represents manufacturer-, year-, month-fixed effects (FEs), respectively.

Using the DID estimation, our primary focus is to look at the coefficients of the interaction terms of AT&T×During and AT&T×After. As we are interested in the response of handset manufacturers competing on product innovation, we include manufacturer-FEs for all models. The manufacturer-FEs allows us to examine a manufacturer's product development and deployment decisions before and after the iPhone while controlling for unobserved firm-specific idiosyncrasies. Since our hypotheses are structured from a manufacturer's perspective, it is imperative to include manufacturer-FEs in all regression models. We also include year- and month-FEs to control for time trend and seasonality because firms' decisions on the technical specifications of their phones may be subject to time trend.

4.4 Results

4.4.1 Product Category Mix Adjustment

The first competitive response we expect from manufacturers is the adjustment of product category assortment between basic phone and smartphone (H4.1a and H4.1b). Evidenced by the later success story, the iPhone was a product that redefined the smartphone as a product category. When the iPhone was released only on the AT&T's network, the competing manufacturers making both basic phones and smartphones have counteracting incentives. In the short run, since now AT&T carries a strong smartphone, manufacturers may want to downplay the disrupted product category (smartphones) by focusing on old product categories (basic phones) (H4.1a). In the long run, however, manufacturers may want to place more smartphones in the AT&T's network because AT&T now becomes known to consumers for better smartphones (H4.1b).

To test these hypotheses, we estimate the change in the product category mix by replacing the dependent variable in Equation (11) with the dummy variable denoting whether the focal phone is basic or smartphone. Table 10 shows the results. To facilitate interpretation, we first report OLS estimates (Models 1-6). All models include manufacturer-FEs and Models 1-3 do not include time-FEs. The only effect strongly significant is that the ratio of smartphones in the product category mix has increased over time. Only 16.9% of phone models were smartphone before the iPhone was launched. 24.6% during the exclusive agreement period and 58.5% after the period of launched phones were smartphones (Model 1). These differences across periods disappear when we include year- and month-FEs (Model 4). However, we find little evidence that manufacturers change the product category mix differentiated across network carriers in this OLS analysis. Only Model 3 weakly suggests that manufacturers released relatively more smartphones on the AT&T's network during and after the exclusive dealing period. This effect also disappears as we control for time trends (Model 6). Although statistically insignificant, all interaction terms except for During $\times$ T-Mobile are positive. It suggests that the major carriers launch more smartphones as time passes in the dataset even after controlling for the underlying time trends.

Table 10: Smartphone Ratio Difference in Differences among Carriers

	1 OLS	2 OLS	3 OLS	4 OLS	5 OLS	6 OLS	7 Logit	8 Logit	9 Logit	10 Logit dy/dx	11 Logit dy/dx	12 Logit dy/dx
(Dummy) During	0.077**	0.068**	0.067**	-0.101	-0.104	-0.103	-0.869**	-0.905**	-0.903**	-0.108*	-0.112*	-0.111*
	(0.011)	(0.006)	(0.005)	(0.075)	(0.075)	(0.072)	(0.329)	(0.341)	(0.338)	(0.044)	(0.045)	(0.043)
(Dummy) After	0.416**	0.400**	0.396**	-0.204	-0.208	-0.212	-1.539	-1.565	-1.645	-0.191	-0.193	-0.202
	(0.057)	(0.059)	(0.058)	(0.216)	(0.221)	(0.222)	(1.031)	(1.090)	(1.058)	(0.126)	(0.133)	(0.128)
(Dummy) AT&T	-0.028	-0.031	-0.029	-0.021	-0.023	-0.021	-0.184	-0.227	-0.193	-0.023	-0.028	-0.024
	(0.016)	(0.020)	(0.020)	(0.016)	(0.013)	(0.012)	(0.304)	(0.256)	(0.238)	(0.037)	(0.030)	(0.028)
During × AT&T	0.056	0.066	0.063†	0.025	0.032	0.030	0.264	0.363	0.314	0.033	0.045	0.039
	(0.034)	(0.037)	(0.035)	(0.032)	(0.033)	(0.032)	(0.383)	(0.383)	(0.388)	(0.046)	(0.045)	(0.045)
After × AT&T	0.168	0.165	0.155†	0.127	0.124	0.117	1.427**	1.599**	1.540**	0.177*	0.197**	0.189**
	(0.106)	(0.104)	(0.087)	(0.115)	(0.114)	(0.097)	(0.533)	(0.450)	(0.430)	(0.069)	(0.060)	(0.057)
(Dummy) Verizon		-0.029	-0.030		-0.018	-0.020		-0.399	-0.424		-0.049	-0.052
		(0.052)	(0.051)		(0.041)	(0.039)		(0.653)	(0.612)		(0.082)	(0.076)
During × Verizon		0.074	0.075		0.048	0.047		0.672	0.674		0.083	0.083
		(0.045)	(0.049)		(0.038)	(0.040)		(0.574)	(0.580)		(0.071)	(0.071)
After × Verizon		0.149	0.143		0.127	0.124		1.619	1.654		0.200	0.203
		(0.124)	(0.126)		(0.113)	(0.113)		(1.089)	(1.076)		(0.139)	(0.137)
(Dummy) T-Mobile			-0.017			-0.018			-0.348			-0.043
			(0.041)			(0.043)			(0.646)			(0.078)
During × T-Mobile			0.010			-0.013			0.098			0.012
			(0.107)			(0.090)			(1.023)			(0.125)
After × T-Mobile			0.071			0.051			1.646**			0.202**
			(0.150)			(0.147)			(0.472)			(0.059)
Constant	0.169**	0.173**	0.175**	0.007	0.009	0.005	-14.660**	-13.931**	-13.741**	N/A	N/A	N/A
	(0.015)	(0.018)	(0.017)	(0.051)	(0.049)	(0.045)	(1.227)	(1.161)	(1.135)			
Manufacturer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Year FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes			
Month FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes			
N	2,691	2,691	2,691	2,691	2,691	2,691	2,589	2,589	2,589			
Log pseudolikelihood							-1,025.98	-1,020.52	-1,017.76			
Adj. R^2 or Pseudo R^2	0.35	0.35	0.35	0.38	0.39	0.39	0.32	0.32	0.32			

Note: Robust standard errors, clustered by manufacturer, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

Since dependent variable is a dummy variable in this case, we need to run logistic regressions with the same specification for methodological rigor. The results reveal much more conclusive evidences for H4.1a and H4.1b. Models 7-9 report raw estimates and Models 10-12 report marginal effects. All logistic regression results include all FEs, so they are equivalent to the OLS results in Models 4-6. Magnitudes are similar between the two estimation methods. However, Models 10-12 show strong statistical significance for the During dummy and the After×AT&T dummy. It means that manufacturers reduced the portion of smartphones in their product mix at first when the iPhone was first launched. It was only after 2011 when manufacturers finally increased smartphone portion in product mix, but those increases are mostly attributable to phones supplied to the AT&T's network.

This set of results portrays the dynamism of manufacturers' reaction to the iPhone in terms of product assortment. At first, they tried to avoid the direct head-to-head competition with the iPhone. As they catch up with the disruption brought by the iPhone after a while, they quickly ramp up the smartphone ratio in their product assortment. AT&T at this time may already have possessed a strong brand associated with smartphones thanks to the iPhone itself and the competition-induced effect shown by this chapter. Thus, AT&T receives higher ratio of smartphones from manufacturers and is able to enjoy the advantage in both quality and quantity over other carriers. Our main findings center around the quality side of the product, but these quantity-based results are in accordance with the main findings.

4.4.2 Better Product for Tougher Competition

When AT&T started to distribute the iPhone, one of the best smartphones of the time, consumers subscribing to AT&T had a superior choice set compared to those using other carriers' network service. Consequently, the AT&T's service network becomes much more competitive from other manufacturers' perspective. AT&T becomes a tougher stage for product innovation contest. In order to be chosen by consumers on AT&T network, competing smartphones should be equipped with superior hardware specifications than the iPhone (H4.2a).

Estimating Equation 11 using OLS regressions, we obtain the results shown in Table 11. The overall innovativeness has increased over time. Based on Model 1, the baseline innovation index was 0.301 before the iPhone. It increased to 0.489 and 0.590 during and after the exclusive period, respectively. Controlling for the year-FEs, we can see that overall innovativeness actually declined after the exclusivity period.

The coefficient of our primary interest, During $\times$ AT&T, is strongly significant in both statistical and economic sense in all models. The results are qualitatively invariant to teasing out major carriers from the baseline (Compare Model 1 to 2-3 or

4 to 5-6). Magnitudes do not vary considerably across different models. This effect that AT&T becomes destination of better products is also robust to controlling for time trends (Compare Models 1-3 to 4-6). During the exclusive contract period, manufacturers supplied phones with the similar level of technical superiority to Verizon and non-major carriers.

Table 11 suppresses the coefficients for time dummies. Usually, time dummies are not to be interpreted, but we find visualizing the DID results overlaid on the time trends helpful to understand the implications of the findings. Figure 22 is constructed using the coefficients within 10% statistical significance from Model 4 in Table 11 with manufacturer-FEs controlled for. This figure succinctly captures how manufacturers become more inclined to launch their better products on the AT&T's network. Surprisingly, the product innovation gap between AT&T and other carriers became even wider after the exclusive contract had ended.

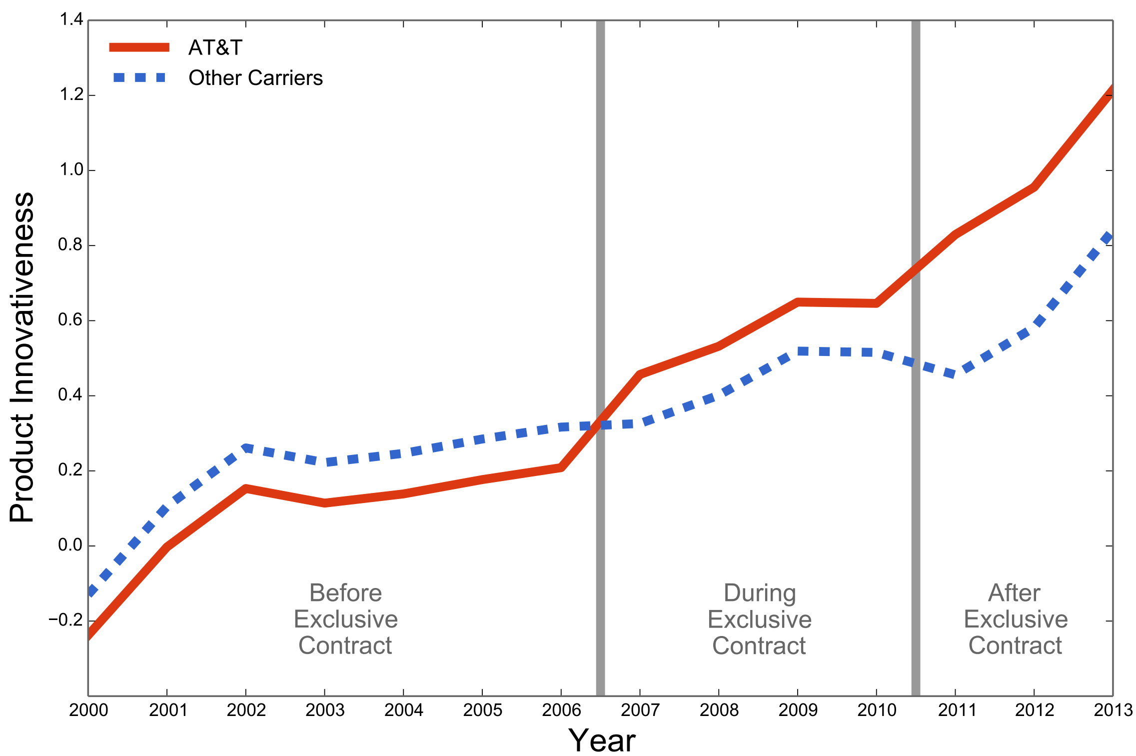


Figure 22: Product Innovativeness Temporal Difference in Differences between AT&T and Other Carriers

Table 11: Product Innovativeness Difference in Differences among Carriers

	1	2	3	4	5	6
(Dummy) During	0.188**	0.196**	0.187**	0.028	0.018	0.011
	(0.042)	(0.039)	(0.041)	(0.055)	(0.053)	(0.053)
(Dummy) After	0.289**	0.285**	0.272**	-0.384*	-0.350*	-0.361*
	(0.057)	(0.051)	(0.059)	(0.139)	(0.139)	(0.134)
(Dummy) AT&T	-0.116*	-0.078†	-0.065†	-0.108*	-0.064	-0.053
	(0.038)	(0.040)	(0.034)	(0.045)	(0.043)	(0.038)
During × AT&T	0.263**	0.264**	0.251**	0.239**	0.239**	0.228**
	(0.031)	(0.027)	(0.029)	(0.040)	(0.037)	(0.039)
After × AT&T	0.528**	0.473**	0.441**	0.482**	0.425**	0.399**
	(0.094)	(0.090)	(0.077)	(0.103)	(0.099)	(0.087)
(Dummy) Verizon		0.264**	0.256**		0.290**	0.283**
		(0.048)	(0.049)		(0.041)	(0.042)
During × Verizon		0.043	0.051		0.010	0.018
		(0.062)	(0.060)		(0.056)	(0.054)
After × Verizon		0.166	0.156		0.125	0.118
		(0.127)	(0.133)		(0.122)	(0.125)
(Dummy) T-Mobile			-0.099			-0.086
			(0.071)			(0.072)
During × T-Mobile			0.112**			0.098**
			(0.018)			(0.028)
After × T-Mobile			0.236			0.196
			(0.151)			(0.150)
Constant	0.301**	0.261**	0.269**	0.438**	0.381**	0.367**
	(0.032)	(0.031)	(0.037)	(0.115)	(0.116)	(0.110)
Manufacturer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
Month FE	No	No	No	Yes	Yes	Yes
N	2,691	2,691	2,691	2,691	2,691	2,691
Adj. R^2	0.17	0.21	0.21	0.21	0.24	0.24

Note: Robust standard errors, clustered by manufacturer, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

Table 11 is based on the innovation index that summarizes the overall goodness of a phone relative to all other preexisting phones. This index consists of seven technology groups: physical, display, computing, battery, camera, connectivity, and sensors. Since each of these technological aspects practically matters in its own way,

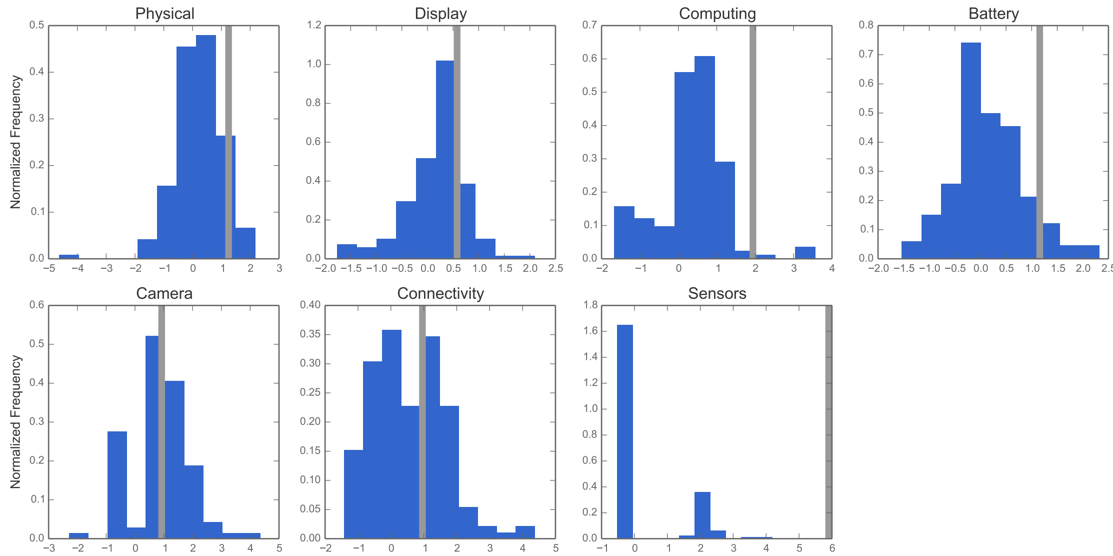


Figure 23: Hardware Strength of the iPhone Relative to Previous Smartphones

it is needed to decompose the measure and trace back which technological aspects drive the observed surge of the innovation index before and after the iPhone's arrival in order to test H4.2b. Before presenting the results decomposed around seven different technology groups, we first show what the iPhone's relative strength is. We expect that competing manufacturers try to keep up with the technology areas that the iPhone excelled in (H4.2b). Figure 23 shows the level of technologies built into the iPhone relative to preexisting smartphones. Each subplot represents one of the seven technological groups. Blue histograms are the distribution of preexisting smartphones' score in each technological group. Thick gray vertical lines are the iPhone's score. The x-axes are z-scores, i.e., standardized scores using the normal distribution. The technological aspects that the iPhone excelled beyond one standard deviation are physical, computing, battery, and sensors.

The sensors chart in particular shows non-normal underlying distribution of preexisting smartphones before the iPhone. This is because many mobile phones before the iPhone did not have built-in sensors, which makes the underlying distribution look like zero-censored. This brings up the concern of inflation of the innovation score of those phones with a number of sensors. To address this concern of measurement, we created an alternative measure of innovativeness not relying on the normality assumption for underlying distribution. We tried percentile scores instead of standardized scores for each technology group, which mitigates non-normal underlying distribution. The results remain robust to this change as correlation of the percentile-based measure to our standardized-score-based measure is above 0.95.

Another way to measure the disruptiveness of the iPhone is to see what new technologies it brought to the market. By "new technologies," we mean the level of technology that the market as a whole has not achieved before the arrival of the iPhone. Comparing the iPhone with other smartphones launched beforehand, we find that the iPhone has introduced new elements in display, computing, and sensors technologies.

With these two ways of capturing the iPhone's technology level in mind, we interpret the results of estimating the same equation with each dependent variable replaced with innovativeness of each individual technology component. Table 12 shows the change in each technological component before and after the exclusive contract began and ended. We find that computing and sensors technologies have improved by a great deal, which should have driven our main results. Three of these four technological domains correspond to the areas that the iPhone had pioneered by incorporating new levels of technologies unachieved by the market beforehand. These results agree to H4.2b in general and tell an in-depth empirical narrative that describes how smartphone technologies have evolved around the exclusive release of the iPhone.

4.4.3 Spillover Beyond Exclusivity Period and Product Category

We interpreted that the innovation boost effect during the exclusive period is due to competition-induced product innovation contest on service network. We expect

Table 12: Component Analysis

	1 Physical	2 Display	3 Computing	4 Battery	5 Camera	6 Connectiv-ity	7 Sensor
(Dummy) During	0.688*	-0.214	-0.274*	0.750**	-0.246†	-0.134	0.186
	(0.255)	(0.159)	(0.115)	(0.114)	(0.114)	(0.085)	(0.330)
(Dummy) After	0.963**	-1.215*	-0.637†	0.565*	-1.114**	-0.285*	-0.340
	(0.288)	(0.439)	(0.316)	(0.255)	(0.274)	(0.127)	(0.406)
(Dummy) AT&T	0.154	0.048	-0.282†	0.310	-0.171	-0.083	-0.535*
	(0.132)	(0.129)	(0.129)	(0.202)	(0.205)	(0.133)	(0.218)
During × AT&T	-0.112	0.072	0.593*	-0.216	0.158	0.180	0.656**
	(0.098)	(0.125)	(0.211)	(0.229)	(0.251)	(0.138)	(0.196)
After × AT&T	-0.187	0.564*	0.899**	-0.045	0.652*	0.199	0.774*
	(0.134)	(0.195)	(0.242)	(0.183)	(0.234)	(0.162)	(0.282)
Constant	-0.060	-1.115**	0.191	-0.199	1.141**	-0.904**	1.681**
	(0.750)	(0.115)	(0.337)	(0.948)	(0.126)	(0.257)	(0.383)
Manufacturer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	771	773	750	765	712	760	771
Adj. R^2	0.11	0.21	0.21	0.24	0.17	0.11	0.27

Note: Manufacturer-, year-, and month-FEs are included in all models. Robust standard errors, clustered by manufacturer, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

that this boost effect, if exists, would persist even after the exclusivity is terminated (H4.3a). One explanation we developed in H4.3a is that as better products are launched on the AT&T's network, a larger number of technology-sensitive consumers subscribe the AT&T service. A larger tech-savvy consumer base of AT&T gives incentive to manufacturers that they deploy their better products on the AT&T network. Thus, the product innovativeness gap among carriers, although triggered by the iPhone, becomes to have nothing to do with the existence of the iPhone on the focal carrier after a certain amount of time passes. Such gap sustains itself through a virtuous cycle created by cross-side feedback links that maintains manufacturers' tendency to supply their better products to AT&T even after the exclusive period.

Table 11 not only shows that the boost effect during the exclusivity period but also after the period. The boost effect after the period (0.528) is actually even greater than the difference during the period (0.263). Note that both numbers measure difference of product innovativeness referencing the pre-exclusivity period as a baseline. This sustained boost effect is robust to different specifications including teasing out other major carriers from the baseline.

Another dimension in which the spillover can occur is product category (H4.3b). We have two product types in our dataset: basic phone and smartphone. Obviously, the product type impacted most by the iPhone would be smartphone. Therefore, it is reasonable to expect innovation boost effect exists for smartphone, while the existence of similar effect for basic phone is ambiguous. It can be positive because manufacturers think AT&T subscribers become more tech-savvy in general. Or, there may be no innovation boost effect for basic phone because each consumer usually has only one phone. So, smartphone users of AT&T are more tech-savvy, while we do not have grounds to think basic phone users are tech-savvy as well. The bottom line is that the difference in innovation index will not be negative.

To examine the spillover across product categories, we run the DID estimation for basic and smartphone separately. Table 13 presents the results from the split-sample analysis. Models 1-3 and 4-6 show the estimation results for smartphone and basic phone, respectively. We confirm AT&T receives not only better smartphones but also better basic phone during and after the exclusive period consistently throughout all models. The magnitude of AT&T's differential gain in product innovativeness of basic phones is about 10% larger than that of smartphones. Another important observation comes from the impact on other major carriers, Verizon in particular. Models 2-3 show that Verizon was supplied with smartphones with relatively inferior technical specifications. The size of drop for Verizon is about the same as the size of gain for AT&T during the same period. When comparing AT&T and Verizon directly, the gap during the exclusive period is much wider than the gap in basic phone.

Table 13: Split Sample Analysis between Smartphone and Basic Phone

	1 Smart	2 Smart	3 Smart	4 Basic	5 Basic	6 Basic
(Dummy) During	0.130	0.187	0.190	0.029	-0.006	-0.010
	(0.096)	(0.144)	(0.145)	(0.073)	(0.066)	(0.069)
(Dummy) After	-0.260	-0.198	-0.188	0.151	0.116	0.111
	(0.174)	(0.171)	(0.170)	(0.153)	(0.160)	(0.166)
(Dummy) AT&T	-0.084	-0.052	-0.029	-0.095	-0.053	-0.048
	(0.080)	(0.094)	(0.077)	(0.059)	(0.057)	(0.053)
During × AT&T	0.193*	0.197*	0.168†	0.210**	0.211**	0.205**
	(0.075)	(0.086)	(0.077)	(0.048)	(0.046)	(0.046)
After × AT&T	0.414**	0.366*	0.330**	0.468**	0.473**	0.470**
	(0.114)	(0.120)	(0.097)	(0.118)	(0.109)	(0.108)
(Dummy) Verizon		0.279**	0.274**		0.288**	0.284**
		(0.060)	(0.064)		(0.042)	(0.042)
During × Verizon		-0.168*	-0.158†		0.087	0.089
		(0.076)	(0.075)		(0.087)	(0.084)
After × Verizon		0.070	0.064		0.079	0.084
		(0.124)	(0.134)		(0.098)	(0.097)
(Dummy) T-Mobile			-0.089			-0.047
			(0.138)			(0.088)
During × T-Mobile			0.161			0.024
			(0.148)			(0.069)
After × T-Mobile			0.168			0.079
			(0.183)			(0.081)
Constant	-0.186	-0.203	-0.198	0.409**	0.361*	0.352**
	(0.212)	(0.198)	(0.198)	(0.115)	(0.114)	(0.104)
Manufacturer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	777	777	777	1,914	1,914	1,914
Adj. R^2	0.27	0.30	0.30	0.14	0.18	0.17

Note: Manufacturer-, year-, and month-FEs are included in all models. Robust standard errors, clustered by manufacturer, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively. Models 1, 2, and 3 contain smartphones; Models 4, 5, and 6 contain basic phones.

4.5 Discussion

4.5.1 Robustness Check with Narrower Split Time Window

In the following sections, we examine the validity of our setting with several robustness checks and present a detailed look into the competitive landscape by showing responses of key individual manufacturers. Since we rely heavily on the empirical setting given by the exclusive dealing, it is imperative that we run a few standard robustness checks for the DID estimation. We run a series of three robustness checks: (1) estimation with narrower time windows, (2) estimation with placebo events, and (3) estimation of prior difference between two groups. First, we start with the estimation using narrower time windows.

The analysis so far has included phones announced during all 14 years between 1999 and 2013. This wide time frame has served its purpose by portraying the overall change in industrial and competitive landscape of product innovation. However, it comes at a cost of blurring the setting for the DID method. Therefore, in order to show the robustness of the results, we need to sharpen our empirical setting. Thus, we estimate Equation (11) on the narrower three-year window around each of the start (Jan 9, 2007) and the end (Jan 11, 2011) of the exclusive contract. One sample consists of phones announced in 2006, 2007, and 2008; the other sample consists of those announced in 2010, 2011, 2012. We lose some statistical power as we have less number of samples to estimate coefficients, but we have a much sharper setting.

Table 14 shows the results from the two-sample analysis. Models 1-3 are from the 2006-2008 sample ($N = 895$), while Models 4-6 from the 2010-2012 sample ($N = 737$). Note that the sample size has reduced about a half compared to the full sample. We identify 53% of product innovation gain for AT&T in smartphone category at the beginning of the exclusive period. We also find similar effect in weaker size and significance when the period ended. On the other hand, we do not find such boost effect for basic phones. Boost effects are mainly attributable to technical specifications of smartphones. This robustness check result is contrary to our main results and we interpret that the sharpened setting produces clear distinction between manufacturers' response in smartphone and basic phone. Comparing the results from the two samples, we make another noteworthy observation regarding the status of AT&T. When the iPhone first appeared in the market by the exclusive contract, phones released on the AT&T network is no better than those on the other carriers' network for both smartphones and basic phones. However, in 2011, AT&T has higher baseline for technical superiority in both product categories. This robustness check result supports our main findings.

Table 14: Robustness Check with Narrower Three-Year Time Window

	1 All	2 Smart	3 Basic	4 All	5 Smart	6 Basic
(Dummy) AT&T	-0.102	-0.178	-0.107	0.169**	0.131†	0.186**
	(0.060)	(0.130)	(0.061)	(0.038)	(0.067)	(0.052)
(Dummy) During	0.086	0.148	0.109			
	(0.069)	(0.201)	(0.062)			
During × AT&T	0.152†	0.340**	0.118			
	(0.071)	(0.080)	(0.071)			
(Dummy) After				-0.338*	-0.379**	0.102†
				(0.130)	(0.113)	(0.051)
After × AT&T				0.151	0.134*	0.065
				(0.086)	(0.053)	(0.174)
Constant	0.364**	0.644**	0.326**	0.512**	0.761**	0.357**
	(0.058)	(0.121)	(0.061)	(0.038)	(0.078)	(0.022)
Manufacturer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	895	159	736	737	379	358
Adj. R^2	0.14	0.13	0.13	0.24	0.18	0.17

Note: Manufacturer-, year-, and month-FEs are included in all models. Robust standard errors, clustered by manufacturer, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively. Models 2 and 5 contain smartphones; Models 3 and 6 contain basic phones; Models 1 and 4 contain both types of phones.

Figure 24 is an alternative representation of the results in Table 14. It emphasizes the difference in product superiority between AT&T and other carriers at two time points of interest. Coefficients significant at least at 10% are used to construct the graphic. All y-axis are drawn to the same scale for convenient comparison. Manufacturers clearly supply to AT&T their best smartphones equipped with superior technical components after the iPhone's exclusive launch on the AT&T network.

4.5.2 Robustness Check with Placebo Events

In addition to narrowing the time window, we measure the estimated effects for placebo events. Estimating the impact on placebo events is a way to check the validity of using the DID method. In order to prevent window overlaps, we further narrow down the time window to the length of one year (180 days before and after the event). Placebo events are arbitrarily chosen as 360 days before and after the actual event dates. We expect not to see significant differences across those placebo event dates.

Table 15 shows the results. Models 1-3 are estimated around the iPhone's exclusive announcement on the AT&T network, while Models 4-6 are around the end of the exclusive period. Note that the number of observations in each model becomes much smaller by an order of magnitude than previous models. These models are estimated on the much more refined scale at the cost of losing statistical power.

Let us first examine the tests around the onset of exclusivity (Models 1-3). Model 2 shows a clear difference in overall product innovativeness before and after the exclusive contract begins. The estimated difference is strongly significant in both statistical and economic senses. Comparing to previous models, the further we narrow down time window, the larger the estimated difference is. This supports our argument that there was a discontinuity in product innovativeness triggered by the introduction of the iPhone. AT&T had been receiving technologically worse smartphones before the iPhone, while manufacturers suddenly increased technical specifications of

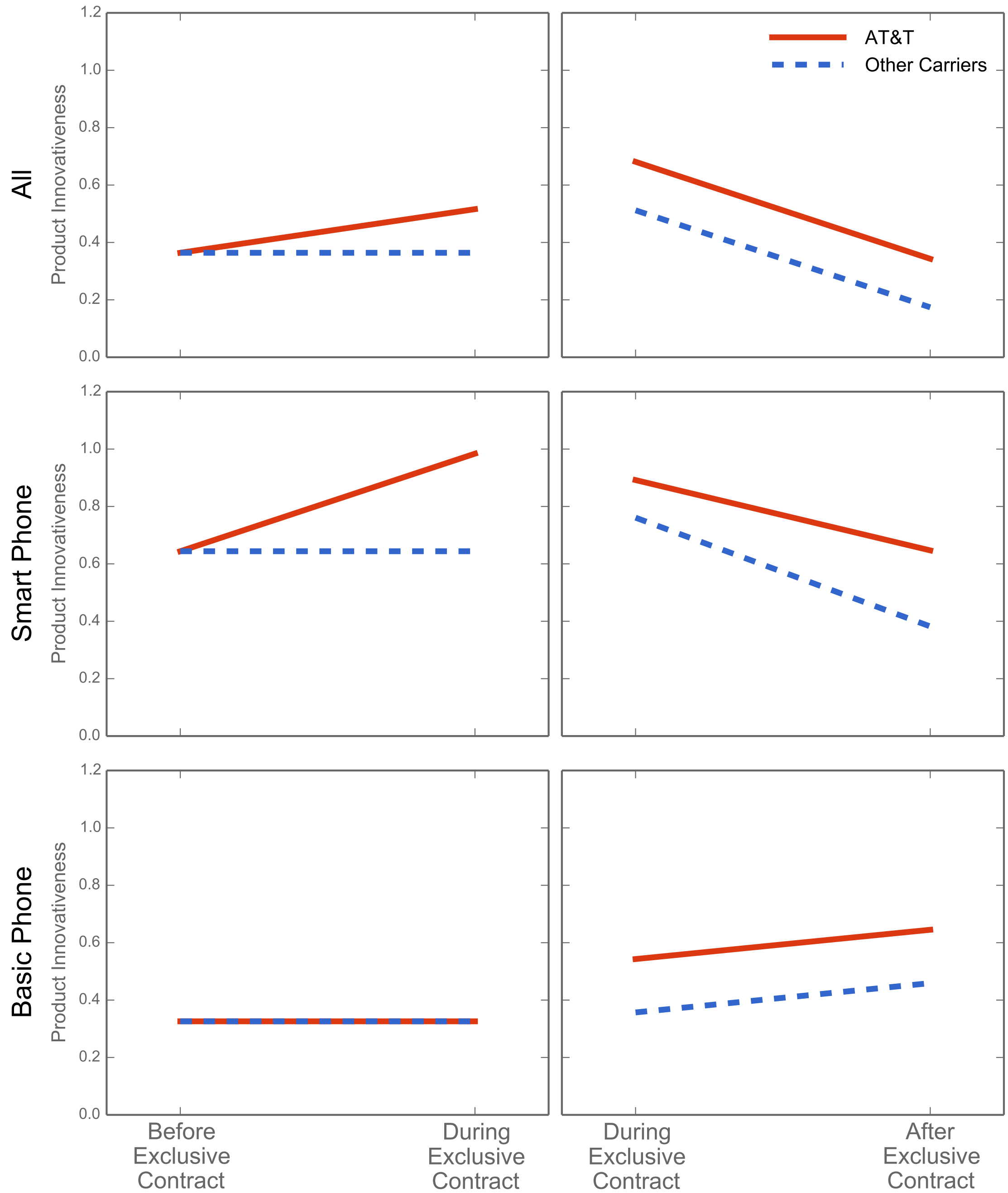


Figure 24: Analysis with 3-year Window

Table 15: Robustness Check with Placebo Events

	1 Placebo Pre	2 Actual	3 Placebo Post	4 Placebo Pre	5 Actual	6 Placebo Post
(Dummy) AT&T	0.118†	-0.359†	0.414	0.332†	0.176*	0.306**
	(0.059)	(0.167)	(0.257)	(0.168)	(0.078)	(0.093)
(Dummy) During	-0.026	0.098	-0.012			
	(0.098)	(0.606)	(0.087)			
During × AT&T	-0.433*	0.805**	-0.324			
	(0.147)	(0.159)	(0.239)			
(Dummy) After				0.344	-0.553*	0.328**
				(0.458)	(0.243)	(0.068)
After × AT&T				-0.107	0.054	-0.170
				(0.320)	(0.236)	(0.170)
Constant	0.307**	-0.005	0.663**	1.034**	1.215**	0.954**
	(0.060)	(0.051)	(0.042)	(0.230)	(0.063)	(0.154)
Manufacturer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	39	54	60	96	126	138
Adj. R^2	0.23	0.16	0.12	0.04	0.15	0.16

Note: Manufacturer-, year-, and month-FEs are included in all models. Robust standard errors, clustered by manufacturer, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

smartphones released on the AT&T network after the iPhone. Models 1 and 3 are estimated around placebo events on January 7, 2006 and 2008, respectively. The interaction term in Model 3 is insignificant as expected, while that in Model 1 is significantly negative. Manufacturers provided technologically inferior smartphones to AT&T over one year prior to the introduction of the iPhone.

We then examine the next set of tests around the end of the exclusive period (Models 4-6). The interaction terms are all insignificant and the magnitude is also negligible compared to those in Models 1-3. Signs are the same: the actual is positive and the placebos are negative. AT&T dummy is positive in all models, suggesting that AT&T in 2010-2012 has already accumulated advantage of carrying superior smartphones from manufacturers. Although we lose significance for the actual event (Model 5), it does not mean that AT&T loses advantage it accumulated during the exclusive period. After all, the sign and magnitude are still largely positive. Unless the sign is significantly negative, the results support that the AT&T's advantage of sourcing superior products continues after the exclusive contract ends.

4.5.3 Comparing Prior Difference as a Robustness Check

Lastly, another robustness check is to see if there are any prior differences across carriers before the iPhone appeared. Although the DID method is designed to take care of prior differences between groups in comparison, it is reassuring to find the groups are relatively homogeneous before a focal event occurs. In our context, what we test is whether manufacturers were already providing AT&T with mobile phones substantially different from those supplied to other carriers in terms of technical specifications. To empirically check for prior differences, we run similar OLS regressions for the subsample defined as for the period before January 9, 2011. We regress the product innovativeness measure onto the sets of dummy variables denoting carrier association and all FEs—manufacturer-, year-, and month-FEs—included. Thus, this test identifies from a manufacturer's perspective whether it was providing different phones to different carriers before the iPhone. Table 16 shows the results.

Each of Models 1-3 show the results when only a dummy variable for major individual carriers used in the main analysis—AT&T, Verizon, and T-Mobile—is included. Manufacturers were supplying slightly inferior products ($p < 10\%$) to AT&T beforehand than other carriers, which is congruent to Figure 22. On the other hand, Verizon was sourcing significantly better products from each manufacturer ($p < 1\%$). Lastly, T-Mobile was treated the same as other carriers on average. These patterns are consistent through Models 4-7 as we recombine carrier dummies in different ways to see if a change in baseline makes any difference. The only noticeable change is that

Table 16: Checking Prior Differences in Product Specifications across Carriers

	1	2	3	4	5	6	7
(Dummy) AT&T	-0.077†			-0.038	-0.064		-0.029
	(0.042)			(0.040)	(0.038)		(0.035)
(Dummy) Verizon		0.282**		0.274**		0.273**	0.268**
		(0.051)		(0.054)		(0.051)	(0.053)
(Dummy) T-Mobile			-0.123		-0.109	-0.089	-0.083
			(0.081)		(0.080)	(0.083)	(0.080)
Constant	0.243†	0.163†	0.156	0.198	0.214†	0.150	0.177
	(0.114)	(0.086)	(0.094)	(0.112)	(0.111)	(0.087)	(0.106)
Manufacturer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	896	896	896	896	896	896	896
Adj. R^2	0.10	0.14	0.11	0.14	0.11	0.14	0.14

Note: Manufacturer-, year-, and month-FEs are included in all models. Robust standard errors, clustered by manufacturer, are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

AT&T dummy now even loses the 10%-level significance as we tease out Verizon or T-Mobile from the baseline group. In sum, these results confirm that manufacturers did not specially treat AT&T by supplying technologically better products before the iPhone appeared on the AT&T's network. Even if there was any prior difference, AT&T was at a disadvantage relative to other carriers—notably Verizon. Therefore, this finding of no prior difference across carriers bolsters our main results signified by the crossing pattern shown in Figure 22.

4.5.4 Manufacturer Heterogeneity in Product Design Responses

All analyses so far included manufacturer-FEs to control for idiosyncrasies of different manufacturers. In order to exploit the factual context of our study—the mobile phone industry, we turn to individual manufacturers and how their product design patterns for AT&T and other carriers evolve differently over time. Top four manufacturers by the number of products from our final sample are Samsung ($N = 874$),

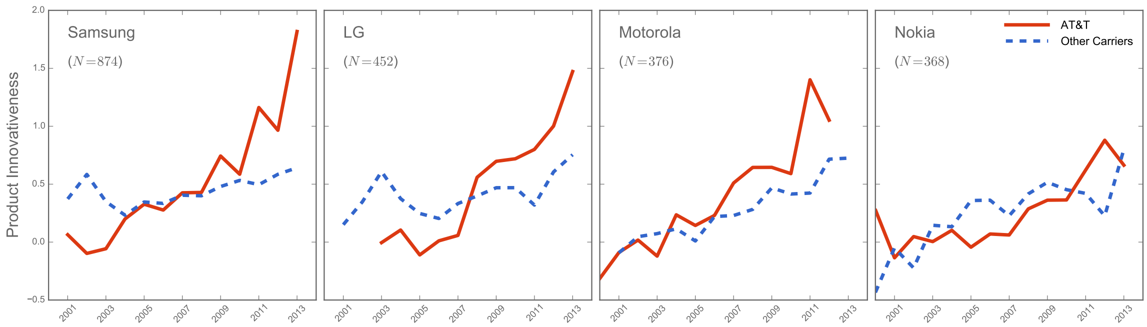


Figure 25: Heterogeneous Responses Across Different Firms

LG ($N = 452$), Motorola ($N = 376$), and Nokia ($N = 368$). All these four companies account for more than 77% of the whole sample, cover the entire time period from 2000 to 2013, and have produced both basic phones and smartphones. Thus, these four manufacturers adequately represent the context of the mobile phone industry. Moreover, we now know the performances and consequences of these four manufacturers in the real-world mobile phone industry in retrospect. Samsung grew as a strong opponent of Apple and LG remained competitive in the market, while the mobile phone division of Motorola was acquired by Google in 2011 and that of Nokia was sold to Microsoft in 2013. Thanks to these factual industrial changes, we believe that it is a meaningful exercise to interpret and draw implications from these manufacturers' design changes over the years.

To operationalize individual manufacturer comparison, we create subsamples for each of four companies. We run the OLS regressions of product innovativeness onto year dummies interacted with the AT&T dummy. Month-FEs are included to control for within-year seasonality. Using coefficients gathered from the regressions, Figure 25 shows different patterns of product characteristics provided to AT&T and other carriers for these four manufacturers.

Representing the largest portion of the sample, Samsung clearly shows a similar pattern to the overall pattern shown in Figure 22. However, its temporal differential pattern exhibits more drastic gap between AT&T and other carriers than the whole sample particularly for the recent years. Two lines are virtually on top of each other from 2004 to 2008 and they diverge afterwards. We identify a similar crossing pattern for LG except that LG shows a relatively wide prior difference before 2008. Motorola had a spike in products given to AT&T in 2011, but the gap reduces back in 2012. On the other hand, Nokia has both lines flat across all years and to our surprise these two lines are in essence the same lines. One consistent feature to note across all subfigures is that the dotted blue lines (technological level of products provided to non-AT&T carriers) are on a similar trend for all four manufacturers. Given that each of four manufacturers accounts for a significant portion of the whole sample, a variety of strategic reactions we observe from this result are noteworthy. While we cannot predicate that these patterns are antecedents of the consequences of the four firms in the current industry, we can entertain the possibility that these patterns coincide with the current standings of the four companies.

4.5.5 Practical Implications

This chapter presents multiple points to reckon for managers working at manufacturers and service providers alike. Manufacturers need to realize the importance of keeping up with other competing products on the service network. The responsiveness is even more critical when a new potentially disrupting product appears in the service network. Once the market starts to get swayed into one direction, it is extremely hard to reverse the trend because of industry and consumer inertia shown in this chapter. Therefore, manufacturers need to keep an eye on new products from competing manufacturers. A disruptive innovation may come from a company that was not deemed as a competitor beforehand. Thus, it is important to possess a wide view on the competitive landscape of the product market and develop comprehensive business intelligence capabilities.

Next, managers working at service providers need to stay in awareness of what new technologies and products are emerging in the neighborhood of the focal service domain. Securing a disruptive innovation for their service network exclusively can ignite the virtuous self-sustaining cycle based on the intensified competition on the manufacturer side. Thus, they can try to source new technologies and products with more aggressive and progressive attitude because of the temporal and horizontal spillover effects shown in this chapter. Once the industry is settled after a disruptive innovation, it stays there for longer than managers imagine. Therefore, it is extremely important for a service provider to secure a good position before a new disruption comes along.

Finally, the result that is new to our previous knowledge is the confirmation of H4.1a and H4.1b that hypothesized about competitive responses to a disruptive innovation by adjusting product mix in short and long terms. It turned out that competing manufacturers first try to avoid the competition with the disruptive technology at the early stage. However, they have to eventually accept the reality transformed by the disruptive technology once the technology landscape is changed. Although we hypothesized about this dynamism, the empirical findings that confirm this hypothesis were refreshing to us.

4.6 Conclusion

Exploiting the effectuation and nullification of the exclusive contract between Apple and AT&T releasing the iPhone, we empirically examine how other manufacturers respond to the abrupt events in terms of their new product design and innovation patterns. We find that a manufacturer first avoided competition with the iPhone by shifting focus to basic phones in product mix, but eventually pursued head-to-head competition in smartphones. In terms of technical specifications, a given manufacturer supplied technologically superior products among all their products, both smartphones and basic phones, to AT&T when the iPhone arrived to the scene.

This imbalance not only persisted but also increased when the exclusive contract had ended.

It is this rare setting of exclusive dealing that allows empirical investigation on manufacturers' responses to the appearance of a disruptive and innovative product on a service network exclusively. Although the setting in this chapter is unique to the mobile technology and industry, the implications of our findings can be applied to other platform-based businesses or two-sided markets. Our study is particularly timely as many exclusive relationships are developing in many industries. In addition to the video game console industry mentioned earlier, Apple TV recently contracted with HBO to exclusively air their content through the device although only for a limited time. Netflix once declining now rejuvenates itself partly thanks to the success of its own development of TV series, "House of Cards." Although there are rooms to study further under what condition developing own exclusive content or having exclusive partnership is good, our findings provide another reason to be more optimistic at the prospect of soliciting an innovative product or partner into the service network. For instance, if you are in the video game console business, you must be particularly aggressive in seeking an exclusive sourcing of high-quality game titles because such arrangement will induce other game developers to exert more effort on the games released on your network as your network becomes an arena of fierce competition.

The direct benefit to AT&T of exclusively introducing the iPhone must have been the increase in subscribers. Subscribers fond of the iPhone may have switched from other network operators or upgraded from a lower-tier product. The former is a new revenue source and the latter contributes to increasing existing revenue streams. Thus, the introduction of the iPhone must have had direct positive revenue implications. What we provide in this chapter evidences that there is a competition-induced secondary spillover benefits of introducing a disruptive product in the service network. Having a strong product in the service network implicitly forces other competing product manufacturers to submit products of a higher caliber in order to stay in business in that particular service network. More important, realizing that firms in one industry can influence the pace of competition among firms in another industry and even harness benefits of that competition will help differently frame the product sourcing strategy in a novel way.

CHAPTER V

ASYMMETRIC FIRM VALUE OF PRODUCT INNOVATION IN THE TRIAD ECOSYSTEM

5.1 Introduction

The value delivered by many products today is not the result of a single firm's endeavor. Rather, a product serves as a conduit of additional value created by service companies in the industry ecosystem. Depending on the roles that each firm assumes in the ecosystem for the product, it derives revenue and profit in different ways. The previous two chapters looked at how manufacturer-designed product technical specifications evolve dynamically in interaction with platform developer and service provider, respectively. This chapter shifts focus to how the market perceives those technological advancements in product characteristics. In the end, we need to evaluate whether product innovation matters at all in dollar terms. We measure the impact of product innovativeness on firm value reflected in the stock market.

The previous two chapters explored bilateral relationships around product innovativeness. Chapter 3 investigated how new product development strategy and new product specifications are influenced by the existence and availability of digital platforms, thus focused on the dyadic relationship between manufacturer and platform developer. Chapter 4, on the other hand, turned to another type of dyadic relationship between manufacturer and service provider by examining how sourcing a highly innovative product benefits service provider as it intensifies product technical specifications competition among manufacturers supplying to the service provider. In this chapter, we close the loop and provide a holistic view of the triadic relationship by looking at all three types of firms in the same setting at once. More specifically, our goal is to quantify the financial rewards of new product introduction by looking at the stock market reaction to the announcement and release events of new products.

This chapter focuses on the firm value of product innovation and aims to identify potentially differential impacts of new product introduction for different types of firms involved in the process. The new product development (NPD) literature widely agrees that new product introduction exerts a positive impact on the manufacturer's stock returns (Bayus et al., 2003). Kalaignanam et al. (2007) extends from single-firm NPD to collaborative NPD and establishes asymmetric firm value implications of NPD to small and large firms, although they do not specifically interpret different roles assumed by alliance participants in the NPD process. This chapter adds to the literature by examining a product category that involves three clearly demarcated roles played by companies from large industries. Similar to the previous two chapters, this chapter examines the smartphone industry where manufacturer, service provider, and platform developer collaborate and compete anchored around the focal product. The value delivered to the end consumer is orchestrated by these three roles of firms. Moreover, only a few studies including Koski and Kretschmer (2010) take into account the technological characteristics of the product of interest. We contribute to the NPD firm value literature by taking into account as many technical specifications as possible, leveraging the product innovativeness measure developed in Equation (7) in Chapter 3. Lastly, our setting affords examination around not only the announcement events of new products but also the release events of the same products, which enables us to empirically and quantitatively measure hype formed by the market when new products are introduced.

Based on aforementioned research focus, the three driving research questions for this chapter are as follows. First, we look for the existence of asymmetric abnormal returns to different roles that the firm assumes in the triad. Following previous evidences (Bayus et al., 2003), we expect positive firm value upon announcement of new products. Then, Kalaignanam et al. (2007) demonstrate such positive abnormal returns to firm value do not occur equally across participants of an NPD alliance. Drawing on their arguments and findings, we also expect that the existence and magnitude of abnormal returns differ across different roles in the triad. Second, we test if such abnormal returns are correlated with the technological superiority of new products. The relationship between product innovativeness and abnormal returns to firm value is relatively under-explored in the current literature of firm value of NPD. Third, we investigate market reactions to the announcement and release of new products separately. The literature documents positive market reactions upon new product announcements. However, it lacks follow-up studies that look at actual release of the products. Since the market can overshoot with hype when a new product is announced, it is worth checking the market reaction when the new product is released into the market.

To operationalize our approach to address the research questions above, we adopt a multi-country event study methodology. While the event study methodology in general has a long history and has been adopted to many different fields of study, running event study in a multi-country setting started receiving attention from the research community only about a decade ago (Park, 2004; Campbell et al., 2010). Event study constructs linear models for individual stock prices with a few market-level factors to define normal behavior on a given day. The deviation from the estimated normal behavior is called abnormal returns and the method statistically tests whether the cumulative average abnormal return (CAAR) over the event period significantly differ from zero. It is the standard methodology employed by the studies investigating the impact of a certain types of events on the firm value. Our multi-country event study method uses three factors (local market index returns, global market index returns, and trade-weighted exchange rates) following Park (2004).

We confirm strong positive impact on firm value to the manufacturer when a new product is announced. On average, the cumulative average abnormal returns (CAAR) is 0.87% throughout the whole ± 10 days around the event day and 0.48% for the (0,+1) window. However, we also find negative market movements (-0.81%) upon actual release that cancel out a significant portion of positive abnormal returns accumulated during the announcement period. The magnitude of negative change upon release is smaller than that of positive impact upon announcement. Still, this up-and-down pattern between announcement and release calls for a conservative interpretation of the positive impact of NPD when only announcement is accounted for. We then observe the relationship between CAAR and technological superiority of the new products measured by product innovativeness. We find strong positive correlations between the two. Thus, when the new product is high in product innovativeness, the positive CAAR for announcement is even greater and the negative CAAR for release is mitigated. For service providers, we find no impact from new product announcement and release on its firm value. The platform developer firm value seems to weakly benefit throughout both announcement and release events. We interpret this asymmetry through the lens of different roles assumed by the firms in the triad relationship in the smartphone industry ecosystem.

The rest of the chapter proceeds as follows. Section 5.2 reviews the methodological literature on multi-country event study and domain literature on the firm value of NPD. Section 5.3 describes our data sources and analysis setups. Section 5.4 reports our main results on abnormal returns to firm value. Section 5.5 discusses implications of our findings and Section 5.6 concludes the chapter.

5.2 Theoretical Background

5.2.1 Multi-Country Event Study Methodology

Event study is an oft-used causal identification methodology to infer monetary valuation of the events having a certain set of characteristics by quantifying abnormal stock market reactions. Since Fama et al. (1969), the methodology has matured and gained sufficient traction in many fields. MacKinlay (1997) provides even a tutorial for how to execute an event study and Binder (1998) reviews a summary of key methodological developments since 1969. The basic premise of event study is that there exists normal behavior of an individual stock price based on a variety of factors such as overall market movement. On top of this normal behavior, each stock price reacts to the new abrupt set of information about the company such as launching a new product or implementing a new policy. Based on the efficient market hypothesis (Fama, 1970), it is assumed that market participants foresee the long-term effects of a certain event, market price absorbs the news, and it reflects such expectations of the market participants. Given the normal behavior, the size of abnormal reaction can be measured.

While providing an essential tool for quantifying the financial value of events, the standard event study has two limitations. First, event study can be used only for companies that are publicly traded. By definition, event study requires time-series price information representing the underlying valuation of the companies of interest. Public stock exchanges provide an excellent setting to conduct an event study. On the other hand, this means that an event study using the stock market reactions cannot examine similar effects on private companies. This is a particularly limiting condition if research questions involve early-stage companies or entrepreneurship ecosystem. This is a fundamental limit that any extension of event study methodology cannot escape. Second, the standard event study model considers only stock markets in a single country. Because of this particular challenge, the literature employing the event study methodology has accumulated empirical evidences mostly from the U.S. stock market only. To overcome this second limitation, the standard event study model can be extended to the multi-country setting. Recent methodological developments have attempted to address this second issue.

In order to extend the standard single-country event study model for a multi-country setting, two challenges arise. First of all, the stock market in a major developed country has its own market index and such local index does not necessarily move in synchronization with other countries' stock market indices due to political, socio-cultural, and macroeconomic differences. Moreover, individual stock price in a local market is often quoted in the corresponding local currency. Thus, a multi-market event study model must address the issues of the local market index as well as the local currency.

Park (2004) outlines an extended event study model for multi-country setting. It takes into account three factors—local market index, global market index, and trade-weighted exchange rate—to model the baseline normal behavior of the individual stock returns. Campbell et al. (2010) further validates the multi-country non-U.S. event study methodology using simulation. As the multi-country event study methodology matures, a new set of research opportunities in the global setting is emerging.

5.2.2 Firm Value of Innovation and Interfirm Alliances

Event study has been extensively used for a variety of management and business policy issues. For instance, measuring the economic value of being an Olympic sponsor (Samitas et al., 2008; Molchanov et al., 2010) or the reputation risk from celebrity endorsement when a scandal breaks out (Knittel and Stango, 2014) are typical issues examined by event study.

Even with the scope narrowed to technology management, NPD, and product innovation, researchers have actively produced a number of articles employing event study up to recent years. The major theme in this literature is to evaluate the impact of a certain type of NPD practices on the stock market performance. Hendricks and Singhal (1997) examine how much missing the promised product introduction date harms the firm value and confirm the negative influence of such delays. Bayus et al.

(2003) investigate the PC industry to find empirical evidence on the positive impact of new product introductions on profitability of the firms. In the pharmaceutical industry where obtaining approval from the regulatory authorities is critical for NPD, Girotra et al. (2007) demonstrate the value of a new drug development project by exploiting the failures in clinical trial as a natural experiment setting. Sood and Tellis (2009) advocate a holistic viewpoint for innovation projects and argue that the total stock market returns for aggregated innovation projects surpass the returns for individual innovation events.

In this literature, a relatively small number of studies specifically focus on the technological characteristics of products. Koski and Kretschmer (2010) conduct an event study in the mobile handset product category. They separate truly innovative new products from imitative new products and find both types of new product introduction have a positive impact on firm value. They operationalize the separation by encoding talk time as technological lead. However, such a measure may be appropriate for mobile phones with only basic functionality (voice communication), but it is rather simplistic for complex products such as smartphones that serve not only voice communication but also data processing and ship with various built-in and third-party applications for diverse tasks. Our study is thus differentiated by associating firm value with the level of technological advancement in multi-faceted technical specifications.

On the other hand, many modern products are embedded in service networks and often times most of their value is realized only when the services are available. Accordingly, innovation in new product offering is increasingly resulting from collaborations or acquisitions among multiple companies. Recognizing the importance of interconnectedness and interdependence between firms in a network setting, researchers have extensively studied the firm value of partnership, alliances, and M&A using event study in the past decade. Seth et al. (2002) are one of the early studies that distinguish positive and negative types of cross-border acquisitions. They empirically demonstrate that an acquiring firm may gain or lose shareholder value depending on the underlying motif of the acquisition. While acquisitions are directional relationships between the acquirer and the target, alliances are more bidirectional where participating firms remain independent after the relationship is established. Forming alliances is viewed favorably from the market and expected to result in overall positive impact on firm value (Anand and Khanna, 2000; Kale et al., 2002). Oxley et al. (2009) even extend the scope to examine how a new alliance influences firm value of the partnering firm's rivals.

Kalaignanam et al. (2007) fuse these two streams of research: firm value of NPD and firm value of alliances. They are first to explore the asymmetric firm value implication from NPD alliances between large and small firms. Our study is in line with the research question they address, but we focus on the asymmetry in the roles that firms assume in such an alliance: manufacturer, service provider, and platform developer. We complement the traditional dyadic analysis (Anand and Khanna, 2000; Kale et al., 2002; Seth et al., 2002) by extending towards the triad perspective in the mobile ecosystem. Our study additionally contributes to this literature by taking into account detailed technological characteristics of the product.

Lastly, an additional angle we bring to the literature is the differentiation between announcement and release of new products. This setting allows us to quantitatively compare market reactions to these two events. The issue of marketing hype—new product announcement as a signaling strategy (Popma et al., 2006; Su and Rao, 2010)—has received a high level of attention from the marketing literature that focuses on NPD practices (Wind and Mahajan, 1987) particularly in the high-tech industry ranging from software such as vaporware (Bayus et al., 2001) to hardware such as DRAM (Popma et al., 2006). Many attempts have been made to develop a theoretical framework for technological hype cycles until recently (van Lente et al., 2013), but most studies examine the effect of the new product announcement (Calantone and Schatzel, 2000; Schatzel and Calantone, 2006) leaving what happens after the actual release of the announced products largely unexplored. We expect to contribute to the understanding of the complete cycle of announcement and release and how the market reacts in the cycle.

5.3 Data and Methods

Table 17 summarizes our data sources. Our dataset largely consists of two parts. The first part is the market data including historical stock prices for individual companies, global and local stock market indices, historical exchange rates, and world trade flow data. Most of the market data comes from the Wharton Research Data Services (WRDS). WRDS is a data service that curates multiple sources of economic and financial data. It provides both web-based and command line interfaces for convenient retrieval of desired datasets. Among many data sources available via WRDS, Compustat Global provides most of global stock market information for our dataset.

We obtain stock returns for individual companies listed in the U.S. stock market from the Center for Research in Security Prices (CRSP) maintained by the University of Chicago. For non-U.S. companies, we retrieve individual stock prices from Compustat Global. They conveniently adjust the individual stock prices for dividends and splits. CRSP also provides equally-weighted U.S. market index and Compustat Global provides non-U.S. local market indices. Morgan Stanley Capital International (MSCI) publishes global market index that includes both U.S. and non-U.S. markets and make the data available through Compustat Global as well. We retrieve the MSCI World Index to represent the global market.

The second part of the dataset is event list and product characteristics: announcement and release dates and detailed technical specifications of smartphones. As in

Table 17: List of Data Sources for Multi-Country Event Study

Stock Market	Stock Returns for Individual Companies (Dividend and Split Adjusted) U.S. Companies: CRSP (University of Chicago) Non-U.S. Companies: Compustat Global
	Local Market Indices U.S. Market Index: Equally-Weighted Index from CRSP Non-U.S. Market Indices: Compustat Global
	Global Market Index MSCI World Index: Compustat Global
	Trade-Weighted Exchange Rate Daily Exchange Rate: Compustat Global Consumer Price Index (CPI): Compustat Global Annual World Trade Data: UN Comtrade
Product	Event and Product Characteristics Announcement and Release Dates: PhoneArena.com Detailed Technical Specifications: PhoneArena.com

Note: CRSP = Center for Research in Security Prices

the previous chapters, the smartphone dataset comes from PhoneArena. It contains the announcement and release timing in date-level resolution. Announcement date is manufacturer-specific information, while release date is carrier-specific information. Thus, if a certain smartphone model is released on multiple carriers, only one announcement date exists for the model but multiple release dates may exist for different carriers. It is also possible that the model was released for different carriers on the same date. The technical specifications break down into seven technology groups: physical (thickness and weight), display (display diagonal, resolution, pixel density, and display panel type), computing (number of cores, CPU clock, RAM, Storage), battery (talk time, stand-by time, battery capacity), connectivity (cellular network speed, Wi-Fi standard speed, and Bluetooth version), camera (main camera resolution, video resolution, and sub camera resolution), and sensors (number of sensors). For the definition of the innovation index, refer to Equation (7) in Chapter 3.

5.3.1 Sample and Variables

Our sample of announcement and release events is constructed from the smartphone data. We start from 1,227 smartphone models from 83 manufacturers. After removing manufacturers that have not released any models in a U.S. carrier service network, we obtain 956 smartphone models. Next, we further refine the sample by excluding observations without both announcement and release dates information. The final smartphone-level sample contains 720 models from 27 manufacturers from both the U.S. and other countries.

We make two further refinements as we proceed to create the lists of events. First, we exclude events if corresponding local and global market indices are not available. Note that we need market data up to about one year prior to the focal event date in order to estimate global market model parameters. Second, we exclude events if multiple products were announced or released on the same day for a given firm in order to avoid confounding effects. Table 18 shows our final event sets in a two-by-three matrix. An event pair is encoded as a line in a file separated by space such as "104604 20050214" where company data item code is followed by date. In this example, "104604" stands for Samsung Electronics.

Table 18: Size of Final Event Sets

	Manufacturer	Service Provider	Platform Developer
Announcement	351 pairs	323 pairs	305 pairs
Release	362 pairs	268 pairs	356 pairs

Table 29 shows the breakdown of companies by country or stock market exchange. Most companies in our sample are listed in the U.S. stock exchanges, while we have significant manufacturers outside the U.S. A few companies play more than one role in product development. For instance, Nokia, BlackBerry, and Apple are both manufacturers and platform developers at the same time. T-Mobile is both manufacturer and service provider. Apart from these notable exceptions, most companies play a single role.

Table 19: Summary of Companies in the Sample by Country

Country (Currency)	Company	Total Number of Events	Count by Firm Type M	SP	PD	Count by Event Type A	R
US (USD)	Google	335	6	0	329	135	200
	Nokia	204	99	0	105	116	88
	Microsoft	148	1	0	147	66	82
	AT&T	137	0	137	0	77	60
	Verizon	119	0	119	0	62	57
	Sprint	107	2	105	0	63	44
	BlackBerry	94	47	0	47	54	40
	Motorola	77	77	0	0	37	40
	U.S. Cellular	70	0	70	0	35	35
	Alltel	63	0	63	0	32	31
	Virgin Mobile	30	0	30	0	16	14
	Apple	26	13	0	13	14	12
	MetroPCS	24	0	24	0	9	15
	Palm	19	14	0	5	15	4
	HP	15	8	0	7	6	9
	Southern LINC	6	0	6	0	3	3
	Dell	4	4	0	0	2	2
	Alcatel	4	4	0	0	1	3
	CellularOne / Dobson	4	0	4	0	4	0
	Qualcomm	2	0	0	2	1	1
	Qwest	2	0	2	0	2	0
	TerreStar	1	1	0	0	1	0
KR (KRW)	Samsung	164	158	0	6	73	91
	LG	77	77	0	0	36	41
JP (JPY)	Sony	13	13	0	0	6	7
	Kyocera	10	10	0	0	4	6
	Casio	3	3	0	0	1	2
CN (CNY)	ZTE	19	19	0	0	12	7
	Huawei	18	18	0	0	10	8
TW (TWD)	HTC	112	112	0	0	52	60
DE (EUR)	T-Mobile	143	28	115	0	75	68

Note: M, SP, PD, A, R stands for manufacturer, service provider, platform developer, announcement, and release, respectively.

U.S. individual stock returns are precomputed by CRSP. Individual returns for non-U.S. companies reported by Compustat Global need to be adjusted. Compustat Global provides daily closing prices ($prccd$) along with cumulative adjustment factors ($ajexdi$) and total return factors ($trfd$). The formula to compute the adjusted price for company i at time t is as follows (Grant and Phung, 2010; Chattopadhyay et al., 2015).

$$\text{Adjusted Price}_{it} = \frac{prccd_{it} \times trfd_{it}}{ajexdi_{it}} \tag{12}$$

Market indices are straightforward variables to define. CRSP provides precomputed daily returns of the U.S. market and we compute daily index returns for global market index and non-U.S. local market indices using the market index data from Compustat Global. We have both local and global market indices needed for estimating the world market model. Since global market by definition includes any local market component, we use orthogonalized global market index with respect to the corresponding local market index. In other words, we take the residuals of the global market index (MSCI World Index) regressed on the local market index. The orthogonalization process is standard in financial studies (Gelos and Wei, 2005).

The last factor for our world market model, trade-weighted real effective exchange rate, warrants detailed explanation on how to construct the variable. Exchange rates are by definition bilateral ratio between one country and another. If we were to include bilateral exchange rates into the market model, the model would be highly crowded with more than two hundred variables. The trade-weighted effective exchange rate aims to solve this problem by computing a single number that representatively summarizes all bilateral exchange rates of the home country. The key idea is to use the trade partner compositions as weighting scheme to take the average of bilateral exchange rates. The standard is to use the geometric mean instead of the arithmetic mean (Buldorini et al., 2002; Loretan, 2005). In addition, the trade-weighted real effective exchange rate even reflects the ratio of consumer price changes between the two countries. The final formula is as follows.

$$\text{Traded-Weighted Nominal FX}_{j,t} = \prod_{k \neq j} \left(\frac{\text{FX}_{j,k,t}}{\text{FX}_{j,k,t-1}} \right)^{w_k} \tag{13}$$

$$\text{Traded-Weighted Real FX}_{j,t} = \prod_{k \neq j} \left(\frac{\text{FX}_{j,k,t}}{\text{FX}_{j,k,t-1}} \left(\frac{\text{CPI}_j}{\text{CPI}_k} \right)^{\frac{1}{360}} \right)^{w_k} \tag{14}$$

where j is a focal country, k is a partner country, and $\text{FX}_{j,k,t}$ denotes one unit of currency$_j$ denominated in currency$_k$ at time t. CPI_j is the annual consumer price index of country j computed from the consumer price index inflation rate in percent. w_k is the ratio of the trade between j and k with respect to the total trade of j.

In theory, for the purpose of running an event study, using real effective exchange rate is contended because of the strong assumption that investors anticipate long-term inflation rate when making investment decision (Park, 2004). In practice, nominal and real effective exchange rates do not make a big difference because we use changes in the exchange rates. CPI is computed annually and does not change within a year. Thus, we use the nominal effective exchange rate for running an event study in this chapter.

Along with product innovativeness as the main explanatory variable, we add control variables that describe firm characteristics. These control variables sourced from Compustat include total assets, capital intensity (capital expenditures divided by total assets), R&D intensity (R&D expenditures divided by total assets), and the number of employees. Compustat records these firm-specific variables on an annual basis. Table 20 shows summary stats for variables used for regressions.

5.3.2 Estimation

We model the normal behavior of individual stock returns based on three factors as follows.

$$R_{ijt} = \alpha_i + \beta_i R_{mjt} + \gamma_i R_{wmt} + \delta_i Z_{jt} + \varepsilon_{ijt} \tag{15}$$

Table 20: Summary Statistics and Pairwise Correlations

Variables	Pairwise Correlations and Descriptive Statistics										
CAR											
Product Innovativeness	0.03										
(Dummy) Manufacturer	-0.01	-0.02									
(Dummy) Service Provider	-0.01	0.05	-0.49								
(Dummy) Released	-0.03	0.09	0.01	-0.06							
(Log) Total Assets	0.03	0.14	-0.36	0.30	0.05						
Capital Intensity	0.01	0.08	-0.03	0.31	0.02	0.20					
R&D Intensity	0.04	-0.13	0.05	-0.60	-0.06	-0.28	-0.38				
# Employees	-0.02	0.00	-0.09	0.65	-0.07	0.74	0.13	-0.78			
Year	0.01	0.34	0.02	0.01	0.15	0.13	0.12	-0.37	-0.15		
Month	0.08	-0.02	0.01	-0.02	0.13	-0.01	0.04	0.01	-0.04	-0.11	
N	1,965	1,965	1,965	1,965	1,965	1,839	1,823	711	1,011	1,965	1,965
Mean	0.21	0.87	0.36	0.30	0.50	10.36	0.06	0.08	112.03	2010.12	6.80
Std. Dev.	9.89	0.47	0.48	0.46	0.50	1.37	0.04	0.06	94.45	1.95	3.24
Min	-41.73	-0.51	0	0	0	4.47	0.01	0.00	6.70	2001	1
Max	95.57	2.19	1	1	1	12.12	0.16	0.17	309.05	2013	12

where R_{ijt} is return of company i in country j at time t. R_{mjt} is return of local market index in country j at time t. R_{wmt} is return of global market index at time t orthogonalized with respect to the local market index of the corresponding country j. Z_{jt} is daily change in trade-weighted exchange rate of country j at time t. We estimate the parameters using observations from -300 days to -46 days of a given event date. Given this market model and estimated parameters, we can define the abnormal return AR_{ijt} of company i in country j on a given day t in the event window as follows.

$$\begin{aligned} AR_{ijt} =& R_{ijt} - \hat{R}_{ijt} \\ =& R_{ijt} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{mjt} + \hat{\gamma}_i R_{wmt} + \hat{\delta}_i Z_{jt}\right) \end{aligned} \tag{16}$$

where $\hat{\alpha}_i, \hat{\beta}_i, \hat{\gamma}_i, \hat{\delta}_i$ denotes estimated parameters for company i from observations in the estimation window. Our event window is from -10 days to $+10$ days around the focal event date.

We run several event studies for the predefined six sets of events using Eventus, a software that can take in custom stock and market data to run event study. WRDS provides a convenient interface to execute Eventus. The main parameters we input to Eventus are listed in Table 21 and Figure 26 graphically illustrates our estimation and event periods around an event date.

Table 21: Inputs used for Eventus

Parameters	Our Settings
Model	Custom Factor Model
Estimation Period End (EST)	-46 days
Minimum Estimation Length (MINESTN)	10 days
Maximum Estimation Length (ESTLEN)	255 days
Estimate Method	OLS
Event Period Start (PRE)	-10 days
Event Period End (POST)	$+10$ days
Alternative Event Windows	$(-10, -2), (-1, 0), (0, +1), (+2, +10)$
	$(0, +3), (0, +5), (-10, +10)$

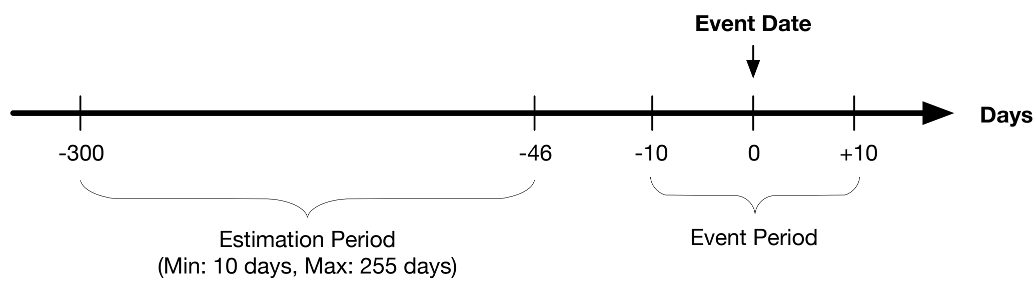


Figure 26: Event and Estimation Periods

Although Eventus is equipped with the capability to run event studies for U.S. companies off the shelf using CRSP data, our purpose is to run event studies in a multi-country setting which is not accommodated by default. We come up with a work around solution to run multi-country event studies using Eventus by constructing data files in a clever way. Eventus provides the custom factor model mode to which we can supply linear factors. The problem is that each company return needs to be estimated based on the corresponding market index. However, the equation to be estimated cannot be modified depending on company attributes such as country.

As a work around, we constructed our dataset supplied to Eventus as shown in Table 22. We assign unique serial integers s for each country for our analysis (U.S.: 0, South Korea: 1, Japan: 2, China: 3, Taiwan: 4). We then shift observations for each country by $-30s$ years (i.e., 10,950 days = 365 days/year × 10 years). Since our smartphone dataset spans for about 15 years, the spacing of 30 years clearly avoids overlaps between countries after shifting. Event dates are shifted using the same logic depending on the country membership of the focal firm.

Table 22: Illustration of Custom Factor Data File for Eventus

Country	Date	Factor1	Factor2	Factor3
US	1997-01-03	0.012477	−0.003246	0.001628
	...	...	...	...
	2013-12-31	0.003915	0.000155	−0.000807
KR	1967-01-16	0.003946	0.002258	−0.002410
	...	...	...	...
	1984-01-10	0.004525	0.002784	0.002032
JP	1937-01-26	0.004372	0.001444	0.003672
	...	...	...	...
	1954-01-19	0.006945	0.003020	−0.002397
CN	1907-02-01	−0.000068	0.006484	0.001916
	...	...	...	...
	1924-01-29	0.000802	0.002826	0.000667
TW	1877-02-13	−0.012863	0.001437	−0.001238
	...	...	...	...
	1894-02-06	0.010356	0.002810	0.000938
DE	1847-02-19	0.003689	0.004777	−0.003120
	...	...	...	...
	1864-02-15	0.006675	0.002632	0.002363

Once we obtain abnormal returns for ±10 days around event dates, we can aggregate them in both temporal and cross-sectional ways. Such aggregated measures are useful to summarize and report findings. Cumulative abnormal return (CAR) is simply the sum of all abnormal returns over the period of interest. CAR over the full event period of 21 days is defined as follows.

$$CAR_{ij} = \sum_{t=-10}^{10} AR_{ijt} \tag{17}$$

Cumulative average abnormal return (CAAR) is computed similarly to CAR except for it averages cross-sectional average of abnormal returns called the average abnormal return (AAR). The definition is as follows.

$$CAAR_\tau = \sum_{t=-10}^{\tau} AAR_t, \quad AAR_t = \frac{\sum_{i=1}^{N} AR_{it}}{N} \tag{18}$$

Once we obtain abnormal returns from event studies and compute cumulative measures, we can compute test statistics on the collections of CARs. We report three test statistics: time-series standard deviation test (CDA), cross-sectional standard deviation test (CSectErr), and generalized sign test (GSignTest). Each test is developed for different purpose. CDA computes a single variance estimate for the entire selection of companies, thus does not take into account unequal variances across companies but avoids cross-sectional correlation problems. CSectErr, on the other hand, estimates variance for each day. Lastly, GSignTest considers only the sign of abnormal returns and gives statistics for whether a significantly more number of companies experience positive abnormal returns on a given day. For a detailed explanation, see Cowan (2007).

After running cross-sectional statistical testings on the collections of CARs, we first test whether product innovativeness has any correlations with CAR. We start with parsimonious models including firm-fixed effects taking care of idiosyncratic firm heterogeneity as follows.

$$CAR_{ijt} = \alpha + \beta \text{Product Innovativeness} + \gamma_j + \delta_t + \theta_t + \varepsilon_i \tag{19}$$

where i, j, t stands for product, company, event time, respectively. α is constant, γ_j is firm-fixed effects, δ_t is year-fixed effects, and θ_t is month-fixed effects. ε_i is the idiosyncratic error term per observation. As an extension to this base model, we add firm-type (manufacturer, service provider, or platform developer) and event-type (announcement or release) dummies and interaction terms with product innovativeness.

We can then relate CARs to various firm-specific predictors of interest by replacing firm-fixed effects with less restrictive country-fixed effects. Since our interest lies in relating product innovativeness with market reactions, innovation index is still the main explanatory variable. Other firm-specific variables such as total assets, number of employees, R&D intensity, and capital intensity are also used. We define the full model as follows.

$$CAR_{ijt} = \alpha + \beta \text{Product Innovativeness} + \beta' X + \gamma'_j + \delta_t + \theta_t + \varepsilon_i \tag{20}$$

where all other notations remain the same with Equation (19) except for X being the matrix of firm-specific control variables and γ'_j being the country-fixed effects.

5.4 Results

5.4.1 Abnormal Returns to Manufacturers

We first examine abnormal returns that occur to manufacturers upon the announcement and release of a smartphone. Figure 27 shows the CAAR accrued to manufacturers over the full event period from -10 to +10 days around the event date. The solid blue line denotes CAAR around the announcement of products, while the dotted red line around the actual release in the network of one of the service providers. After day 0, the solid blue line clearly moves upward, while the dotted red line downward. We can interpret that market reaction is generally positive when a manufacturer announces a new smartphone, while it turns negatively overall when people can actually see can use the product released in the market. Note that the initial negative movement upon release is delayed by 3 days from the event date, which implies that it takes some time for the market to evaluate an actual product and digest how the general public rates the product after using it. The magnitudes are symmetric between two types of events (+0.87% for announcement and -0.81% for release), which suggests that the positive impact measured at the announcement of a new product may not as high as estimated unless disappointment upon release is not accounted for.

Table 23 shows the results from the statistical tests for CAAR on different subsets of time window within the event period. Periods are chosen to provide a sharpened

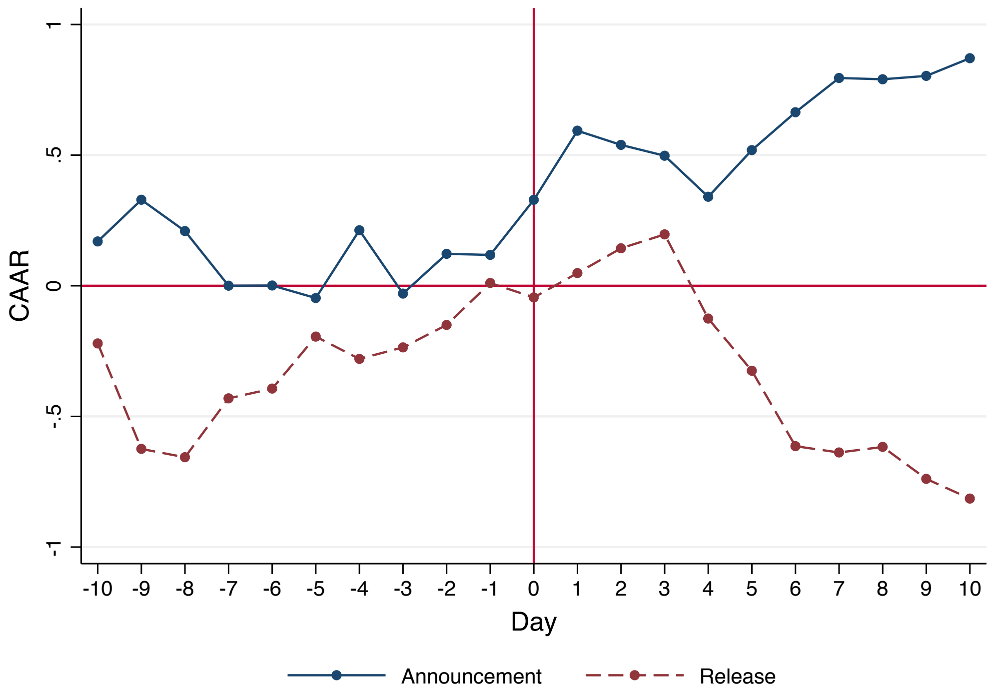


Figure 27: CAAR to Manufacturer

look into the narrow time window around the event date. Periods such as (-10,-2) and (-1,0) are chosen to examine abnormal returns before the event, while others are for post-event examination.

We start with the market reaction to the announcement events, the upper pane of the table. CAAR between day 0 and day 1 is significantly positive (0.48%) on new product announcement. Other post-event periods, (0,+3) and (0,+5), also indicate positive market movements. Overall, the (-10,10) window summarizes CAAR over the full 21 days as 0.87%. On the other hand, the market responds in the opposite way when a new product is actually released in the service network as shown in the lower pane of the table. We observe a small positive effect (0.11%) in the (-1,0) window, followed by a strong and large negative reaction (-0.86%) in the (+2,+10) window. In sum, we observe from the (-10,+10) window a significant negative impact (-0.81%) on manufacturer firm value upon actual release of the new smartphone.

Table 23: Statistical Tests on CAR to Manufacturer

Event Type	Days	N	Mean CAR	CDA	CSectErr	GSignTest
Announced	(-10,-2)	351	0.12%	0.323	0.383	1.620†
	(-1,0)	351	0.21%	1.16	1.006	0.766
	(0,+1)	351	0.48%	2.667**	1.411†	-0.089
	(+2,+10)	351	0.28%	0.733	0.708	0.552
	(0,+3)	351	0.38%	1.506†	0.973	0.872
	(0,+5)	351	0.40%	1.299†	0.849	0.231
	(-10,+10)	351	0.87%	1.507†	1.370†	1.193
Released	(-10,-2)	362	-0.15%	-0.421	-0.439	-0.651
	(-1,0)	362	0.11%	0.628	0.622	1.874*
	(0,+1)	362	0.04%	0.226	0.22	1.033
	(+2,+10)	362	-0.86%	-2.425**	-2.242*	-0.335
	(0,+3)	362	0.19%	0.784	0.642	1.453†
	(0,+5)	362	-0.34%	-1.156	-1.032	0.086
	(-10,+10)	362	-0.81%	-1.498†	-1.444†	-0.861

Note: Robust standard errors are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

5.4.2 Abnormal Returns to Service Providers

Next, we turn to the impact of new product introduction the service provider side. Figure 28 shows CAAR on service provider firm value. Unlike the manufacturer's case, the solid blue line is largely flat across all 21 days. The small peak that turns positive on +2 day is eroded afterwards. On the release side, we detect more variation than the announcement case. We discover a strong peak about a week (-6 day) ago from the event date, followed by a negative movement occurs after the actual release date and cancels out the initial positive effect. One possible reason why we do not see any abnormal returns across the event window is that the market does not know the carrier information at the time of announcement of the product. This is especially the case when a new product is released on multiple carriers in a staged manner. The iPhone is a good example of such a case. The iPhone was released only on the AT&T's network initially and on the Verizon's network four years later. It is not plausible that market at the time of announcement expected the iPhone would be eventually released on other service providers than AT&T. However, unlike the iPhone, many usual phones are not specifically and exclusively targeting a certain set of service providers in advance. In this case, it is more plausible to assume that market just does not pay much attention to such a usual new product. In general, it is understandable that service provider firm value is influenced only when a new product is actually released to end consumers.

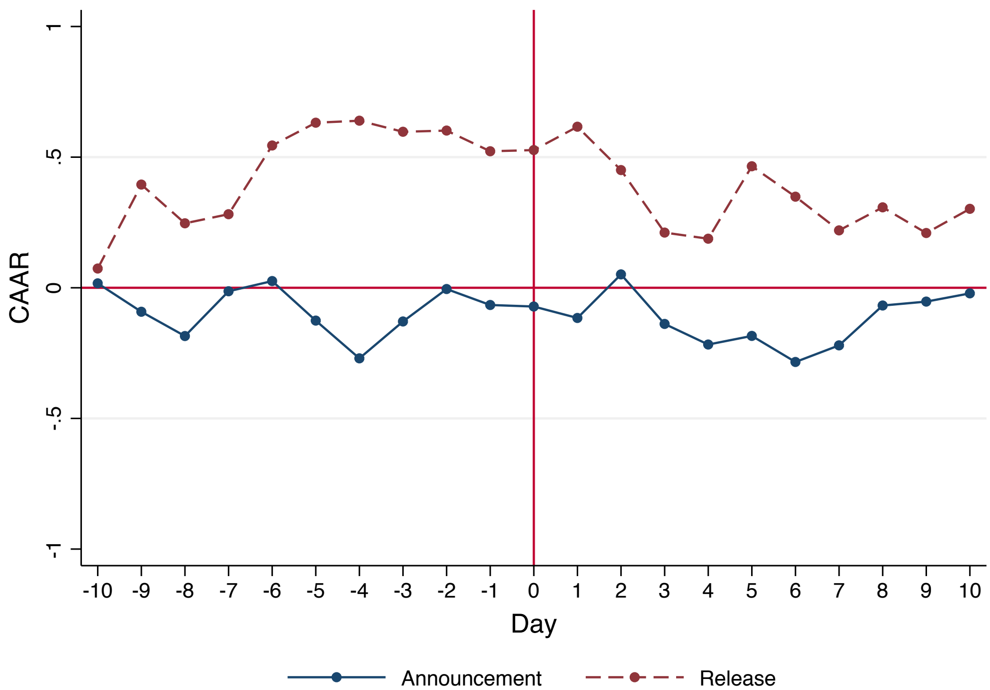


Figure 28: CAAR to Service Providers

Table 24 shows the results of statistical testing for service provider firm value. As we expected by inspecting Figure 28, the CAR is almost indistinguishable from zero when a new smartphone is announced. The different time windows report the mean CARs smaller in magnitude than the manufacturer case. We still obtain a few significant observations from the generalized sign tests (GSignTest) for the post-event windows: (0,+3) and (0,+5). Note that the signs of GSignTest and the other two test statistics are opposite. During the post-event period, CAR tends to be positive but the mean value is insignificantly negative probably because of a few large negative CARs in that time window.

For release-type events, we identify a strong positive (0.60%) bump during the period of (-10,2). Although statistically insignificant, this positive impact in the pre-event period is canceled out with negative impact over post-event periods. The positive impact is about twice larger in magnitude than the negative impact, leaving us with the overall positive impact (0.30%) for the period of (-10,10) window. The significant positive abnormal returns before the release date suggests that the information is leaked to the market about a week before the actual release.

Table 24: Statistical Tests on CAR to Service Provider

Event Type	Days	N	Mean CAR	CDA	CSectErr	GSignTest
Announced	(-10,-2)	323	0.00%	-0.015	-0.02	-0.012
	(-1,0)	323	-0.07%	-0.431	-0.412	0.545
	(0,+1)	323	-0.05%	-0.32	-0.322	0.322
	(+2,+10)	323	0.09%	0.286	0.329	0.879
	(0,+3)	323	-0.07%	-0.33	-0.346	1.769*
	(0,+5)	323	-0.12%	-0.441	-0.485	2.103*
	(-10,+10)	323	-0.02%	-0.043	-0.048	0.545
Released	(-10,-2)	268	0.60%	1.575†	1.482†	2.634**
	(-1,0)	268	-0.07%	-0.414	-0.41	0.8
	(0,+1)	268	0.09%	0.521	0.512	-0.3
	(+2,+10)	268	-0.31%	-0.821	-0.986	-0.911
	(0,+3)	268	-0.31%	-1.219	-1.234	0.067
	(0,+5)	268	-0.06%	-0.184	-0.197	0.067
	(-10,+10)	268	0.30%	0.519	0.478	1.167

Note: Robust standard errors are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

5.4.3 Abnormal Returns to Platform Developer

Lastly, we investigate the impact of new smartphone announcement and release on the platform developer firm value. Figure 29 shows overall upward trends in CAAR for platform developers when a new smartphone is both announced and released.

We observe a positive bump about a week ahead of the release event. Such early reactions are not detected for manufacturers. Also, overall positive reaction after release is unique to platform developer.

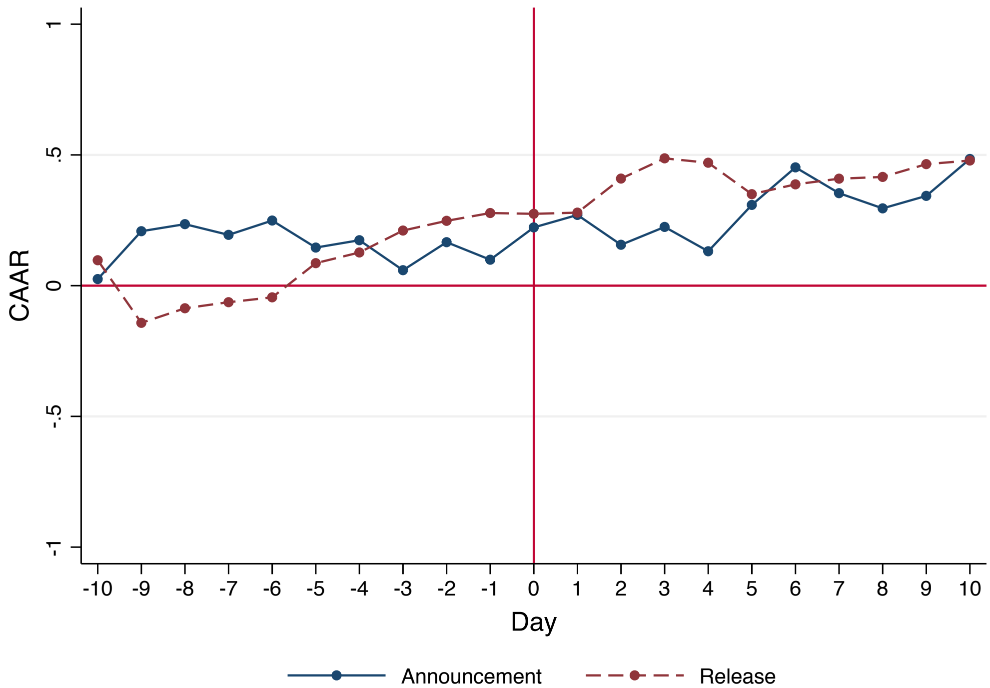


Figure 29: CAAR to Platform Developer

Table 25 shows the results from statistical tests on the CARs to platform developers. Although upward patterns are identified from the figure, we do not have much statistically significant result on the other hand. This insignificance is rather surprising as mean CAR clearly suggests positive abnormal returns for both announcement and release events. It suggests that the standard errors of CARs are greater than the mean value. That is, platform developers experience large positive abnormal returns as often as large negative abnormal returns. In sum, based on the mean CAR, the magnitude of positive market reactions upon announcement (0.48%) and release (0.48%) is about a half of that of manufacturers.

Table 25: Statistical Tests on CAR to Platform Developer

Event Type	Days	N	Mean CAR	CDA	CSectErr	GSignTest
Announced	(-10,-2)	305	0.17%	0.526	0.521	1.298†
	(-1,0)	305	0.06%	0.38	0.361	0.381
	(0,+1)	305	0.17%	1.15	0.97	0.725
	(+2,+10)	305	0.21%	0.677	0.624	-0.191
	(0,+3)	305	0.13%	0.595	0.55	-0.077
	(0,+5)	305	0.21%	0.812	0.7	-0.077
	(-10,+10)	305	0.48%	1.003	0.941	0.954
Released	(-10,-2)	356	0.25%	0.82	0.922	0.79
	(-1,0)	356	0.03%	0.189	0.184	1.744*
	(0,+1)	356	0.00%	0.01	0.01	-1.012
	(+2,+10)	356	0.20%	0.659	0.677	-0.694
	(0,+3)	356	0.21%	1.038	0.834	-0.164
	(0,+5)	356	0.07%	0.292	0.264	0.684
	(-10,+10)	356	0.48%	1.036	1.056	-0.164

Note: Robust standard errors are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

5.4.4 Relationship between Abnormal Returns and Product Innovativeness

The previous subsections examine abnormal returns for each type of firms and events. In those subsections, we focus on whether abnormal returns are detected upon events and the magnitude of such abnormal returns. We are interested not only in the abnormal returns but also in the relationship between the abnormal returns and the technological innovativeness of the corresponding product. Accordingly, we perform regression analyses with CAR on the left-hand side and product innovativeness on the right-hand side along with other control variables following Equation (19).

We construct the full sample dataset by merging all types of firms and events and include dummy variables denoting firm types and event types. Platform developer dummy and announcement event dummy form the baseline for estimation. Table 26 reports the overall effect of product innovativeness on CAR occurring from different

Table 26: Overall Relationship between Product Innovativeness and CAR

	1	2	3	4
Innovation Index	1.639**	1.816†	1.637**	2.149†
	(0.501)	(1.002)	(0.500)	(1.252)
(Dummy) Manufacturer	0.461	-0.851	1.030	-0.670
	(1.182)	(1.442)	(1.273)	(1.801)
Index × M		1.690		2.266
		(1.136)		(1.762)
(Dummy) Service Provider	0.597	1.167	0.362	1.988
	(1.755)	(1.989)	(1.807)	(2.168)
Index × SP		-0.833		-2.043
		(1.092)		(1.450)
(Dummy) Released Event	-0.568	0.183	-0.202	1.168
	(0.481)	(0.974)	(0.693)	(1.504)
Index × Released		-0.835		-1.538
		(0.937)		(1.524)
(Dummy) M × Released			-1.290	-0.623
			(1.035)	(2.110)
Index × M × Released				-0.903
				(2.207)
(Dummy) SP × Released			0.362	-2.056
			(1.034)	(2.285)
Index × SP × Released				2.769
				(2.126)
Constant	-23.436**	-22.922**	-23.728**	-23.130**
	(1.696)	(1.799)	(1.734)	(1.871)
Firm-FE	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes
Month-FE	Yes	Yes	Yes	Yes
Country-FE	N/A	N/A	N/A	N/A
N	1,965	1,965	1,965	1,965
F-stat	35.52	30.88	29.02	29.20
Adj. R^2	0.07	0.07	0.07	0.07

Note: Robust standard errors are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

types of events. All models include firm-, year-, and month-fixed effects. Firm-FE controls for unobserved heterogeneity in firm characteristics and idiosyncrasies.

Year-FE is supposed to control for year-by-year time trends and month-FE is to control for seasonality in product announcement and release. We find a strong positive correlation between product innovativeness and abnormal returns in firm value. Based on the estimate from Model 1 (1.639, $p < 0.01$), a new smartphone with one standard deviation superior technical specifications compared to preexisting historical models is associated with 1.639%p higher CAR over the event period. According to the estimates of the interaction terms, we do not find a differential impact of product innovation across different firm types or event types (Models 2-4).

To take a closer look at the differential impact of product innovativeness on different types of firms and events, we run split-sample analyses. Instead of controlling for firm types with dummy variables, we split the full sample into subsamples based on the types of firms and events. Models 1-6 in Table 27 correspond to Cartesian product combinations of three firm types (manufacturer, service provider, and platform developer) and two event types (announcement and release). We find a significant positive relationship between product innovativeness and CAR only for manufacturer firm value. One thing to note is that such positive relationship exists not only for the announcement events but also for the release events. Recalling that manufacturer firm value suffers negative CAAR upon new product release overall, we find that such negative impact is mitigated if the product is highly innovative in its technical specifications. For other types of firms, products with higher innovativeness are associated with higher CAR, although statistically insignificant.

The regression models so far include firm-FE, which prevents us from examining how firm characteristics are interacting with product innovativeness on CAAR. As a next step, we want to understand how firm characteristics are interacting with product innovativeness to influence CAR. Table 28 reports regression models with firm characteristics such as total assets, capital intensity, R&D intensity, and number of employees. Instead of the firm-fixed effects, we include the country-fixed effects

Table 27: Split Sample Analyses across Firm Types and Event Types

	1	2	3	4	5	6
	Manufacturer		Service Provider		Platform Developer	
	Announced	Released	Announced	Released	Announced	Released
Innovation Index	4.814**	2.151†	0.171	0.478	1.522	1.074
	(1.842)	(1.200)	(0.930)	(1.367)	(1.242)	(0.948)
Constant	-21.077**	-2.319	-2.305	-4.719†	-23.136**	-3.028†
	(3.507)	(2.643)	(2.558)	(2.432)	(2.512)	(1.623)
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-FE	N/A	N/A	N/A	N/A	N/A	N/A
N	351	362	323	268	305	356
F-stat	16.83	1.47	2.37	2.96	25.11	3.87
Adj. R^2	0.14	0.04	0.07	0.09	0.14	0.11

Note: Robust standard errors are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

to control for market-specific idiosyncrasies. Model 1 confirms our previous results that product innovativeness is positively correlated with CAAR. Model 2 shows the interactions between product innovativeness and various firm characteristics. It turns out that firms with high R&D intensity have an even stronger association between product innovativeness and CAAR. In other words, when firms with high R&D intensity announces or released a new smartphone technologically superior to preexisting models, the market reacts strongly positively to such news.

Table 28: Firm Characteristics

	1	2
Innovation Index	1.372**	6.780
	(0.489)	(4.420)
(Log) Total Assets	-0.254	0.346
	(0.328)	(0.364)
Capital Intensity	-8.384	1.790
	(9.623)	(13.602)
R&D Intensity	6.468	-27.937**
	(6.007)	(9.684)
# Employees	0.002	-0.006
	(0.003)	(0.005)
Innovation Index		-0.609
× (Log) Total Assets		(0.419)
Innovation Index		-11.757
× Capital Intensity		(10.613)
Innovation Index		44.252**
× R&D Intensity		(11.951)
Innovation Index		0.008†
× # Employees		(0.004)
(Dummy) Manufacturer	-0.027	0.111
	(0.774)	(0.767)
(Dummy) Service Provider	-0.219	-0.101
	(0.695)	(0.695)
(Dummy) Released Event	-0.590	-0.668
	(0.472)	(0.467)
Constant	-21.304**	-22.399**
	(3.574)	(3.447)
Firm-FE	No	No
Year-FE	Yes	Yes
Month-FE	Yes	Yes
Country-FE	Yes	Yes
N	1,823	1,823
F-stat	509.98	439.81
Adj. R^2	0.08	0.09

Note: Robust standard errors are in parentheses. †, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

5.5 *Discussion*

5.5.1 Three Different Roles for a Single Product Category

We have examined abnormal returns to firm value of manufacturers, service providers, and platform developers upon announcement and release of a new product. We have also looked at the relationship between technological superiority measured by product innovativeness and market reaction captured as abnormal returns. The results clearly demarcate differential impacts of new product launches across different types of companies involved in the NPD process. Table 29 summarizes the abnormal returns we identify using event study. We discuss interpretation and potential reasons for the asymmetric results across three different roles around the smartphone product category.

Table 29: Summary of Identified Abnormal Returns

	Manufacturer	Service Provider	Platform Developer
Announcement	Strongly Positive	Neutral	Weakly Positive
Release	Strongly Negative	Neutral	Weakly Positive

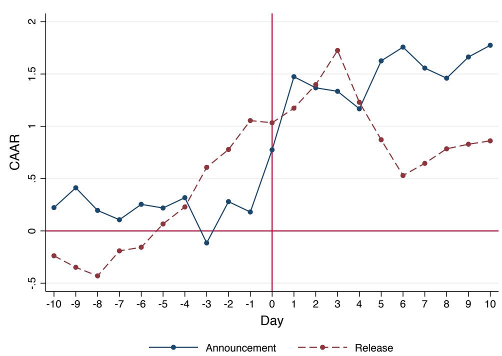
A strongly positive CAAR for the manufacturer upon announcing a new product is rather expected and confirms our intuition. What is less obvious is a strong negative CAAR when the product is actually released into the market. Manufacturer firm value is net positive throughout announcement and release events, but such positive effects may be exaggerated if only announcement events are taken into account. Our findings confirm that the market can be hyped and potentially overshoot when a new product is announced particularly if technical specifications are breakthrough to the current innovation landscape. When the product does not meet the expectation of consumers, such a product launch may do more harm than good for the manufacturer firm value because of disappointment after release. Furthermore, the positive correlation between product innovativeness with CAR is amplified for the companies with high R&D intensity. Given that companies with high R&D intensity are likely to have generated technologically superior products, the market reacts more enthusiastically when these companies meet the expectation by launching uber products.

Nonexistence of significant CAAR for service providers upon new product launches warrants further discussion. One possible reason is that the business model of service providers is not much related to the product itself. Service providers derive revenue primarily based on subscription fees for access to cellular networks. Unless the product is clearly disruptive to the market like the iPhone as seen in Chapter 4, the market does not seem to view that announcement and release of a new smartphone are relevant to the core for the profitability of the service providers. Moreover, the main service that network carriers provide to consumers is calling and data connection service through cellular networks. For most smartphones, technological advancement of the product itself is not a limiting factor for the quality of these cellular network services.

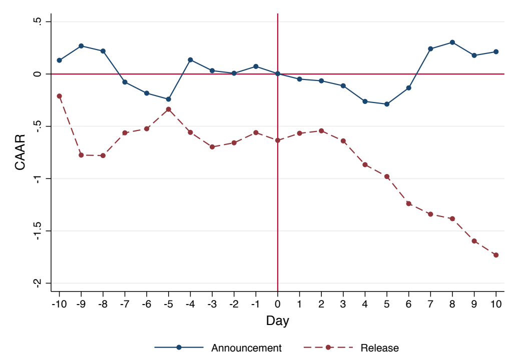
On the other hand, platform providers are more closely dependent on the technical specifications of smartphones. Both operating systems as a platform and third-party apps available on the OS are bounded by various technological components built into the product. Thus, we can expect that firm value of platform developers reacts more sensitively to new product rollouts than that of service providers does. More importantly, unlike network services provided by carriers, OS and apps are not device-agnostic. Some apps available in one device are not necessarily available in other devices. Thus, offering the platform through many device models to maintain network effects is critical to the platform developer's business. That may be why the market reacts positively in general to the news that a new product will ship with a certain OS.

5.5.2 Differential Effects across Countries

We employ the multi-country event study as a central methodology for this chapter. This approach operates on the premise that stock markets around the world are connected and synchronized via instantaneous information propagation. It is worth checking heterogeneous market reactions across different countries, particularly comparing U.S.-based companies to non-U.S. ones because our dataset can be nearly bisected by the U.S. vs. non-U.S. dichotomy. We thus run another event study with split samples of manufacturers divided by whether the company is listed on the U.S. stock exchanges or on the non-U.S. markets. Figure 30(a) shows CAAR to U.S. manufacturers and Figure 30(b) shows CAAR to non-U.S. manufacturers.



(a) U.S Manufacturers



(b) Non-U.S. Manufacturers

Figure 30: Differential CAAR to Manufacturers by Country

For announcement events, we can see that the positive CAAR is mainly from smartphones released by U.S. manufacturers. The firm value of the non-U.S. manufacturers is almost insensitive to announcement of new products. On the other hand, the release of new smartphones negatively affects firm value of both types after the event date. The difference is that the U.S. manufacturers accumulate positive abnormal returns before the actual release of the product, while the non-U.S. manufacturers suffer from successive negative abnormal returns all the way through the event period. One possible account for this stark difference is U.S. manufacturers tend to launch new smartphones with relatively superior technical specifications. This explanation relates this cross-country difference to the positive relationship between product innovativeness and CAR.

5.5.3 Practical Implications

In this study, we identify three types of firms involved in the value proposition of smartphones. In practice, however, the same firm may play multiple roles in the triad. Apple is a representative example of such companies. Apple is a smartphone manufacturer without doubt, but it is also a digital platform developer at the same time. In a sense, it is specialized in building products that are seamlessly fused with digital platforms. Moreover, Apple is the largest public company in terms of market capitalization as of 2015, which suggests it has a disproportionate amount of influence to the market by launching a new product or service. This chapter does not explicitly consider the unique impact posed by giant companies like Apple.

This chapter also has relevant to individual investors managing portfolio focusing on technology companies. The stock price of manufacturers in particular exhibit up and down around a cycle of new product introduction. Investors may be able to reap profits over the cycle of patterns. For managers working at individual companies in the triad, our study in this chapter gives a warning that introducing premature or below-average products may lead to severely negative impact on the firm stock performance.

Three findings from this chapter are unexpected to us. First, the stock prices of service providers and platform developers are statistically insensitive to new product announcements and releases after all. As a result, we have weaker empirical results in terms of statistical significance than we hoped for. We attributed this insensitivity to different business models around the smartphone product category. Second, the stock prices of companies in all three different roles react in different directions upon announcements and releases of new products. Lastly, we did not expect significant negative reactions on the manufacturer stock prices after product releases.

5.6 Conclusion

The smartphone industry is a unique setting in that it involves three large industries centered around a single product category. Manufacturer designs physical devices, service provider provides cellular network services, and platform developer builds software that runs the devices. Each type of firms reaps profit from this product in three different ways. The manufacturer sells products based on one-time unit-based pricing. The service provider generates revenue streams from subscription-based fee structure. The platform developer takes cut from sales of third-party apps. Depending on these different business models, new product launches have varying implications on firm value across different types of firms.

We adopt a multi-country event study method to examine such differential impact of new product launches around the announcement and release events. The smartphone industry is a plausible setting to apply event study because firms involved in the industry are relatively large and in many cases publicly listed on a stock market around the world. We find that strong positive abnormal returns to the manufacturer firm value upon announcement, but we also find strong negative abnormal returns when the product is actually released. The positive effect is boosted and the negative effect is mitigated when the product is technologically superior to preexisting models. The positive impact of product innovativeness on firm value is mainly channeled through companies with high R&D intensity. Thus, our findings have stronger implications to companies with high R&D intensity than to those with low R&D intensity. Service provider firm value turns out to be unrelated to new product launches and platform developer firm value is affected weakly positively.

Our study contributes to the mobile ecosystem literature and the new product announcement marketing literature in two ways. First, we are first to systematically analyze differential impacts of new product introduction on firm value depending on firm types in the industry triad. Second, we measure the impact of not only announcement events but also release events. The literature on new product launching strategy has accumulated theories and empirical evidences that warn of potential harm of not meeting market expectations when a new product is introduced to the market. We quantify the market hype about a new product by comparing the two sequential stages in the typical new product rollout process to provide a more comprehensive view around the practice of new product introduction. Lastly, one minor contribution is that we document and apply event study in a multi-country setting in the NPD context. Up to date, a majority of NPD studies involves U.S. companies only. We expect multi-country perspective will be increasingly important as NPD collaboration becomes global. We hope our study can provide a guide for the future studies investigating firm value implications of NPD practice involving companies from all around the world.

As an extension of this study, we see three immediate research opportunities in the future. In this chapter, we intentionally focus on the smartphone product category excluding basic or feature phones because the manufacturer-service provider-platform developer triad is the central configuration we want to investigate. Future studies may consider comparing our study with market reactions to the introduction of basic or feature phones. Another possibility is to look deeper into the development of OS and examine how releases of new updates to the software platform affect firm value. Lastly, many web sites collect user reviews about various aspects of a product. Such reviews may contain information about the qualitative and nuanced characteristics of the product not captured in technical specifications. We can take into account consumer evaluations and reviews and use rating scores or text analytics to capture the qualitative aspects. Thus, associating how the consumer market perceives a new product with abnormal returns can be another future extension of the study in this chapter.

CHAPTER VI

RECONSTRUCTING BUSINESS ECOSYSTEM USING CLUSTERING AND SIMULATION

6.1 Introduction

The previous three chapters examined the interaction between product innovativeness and interfirm relationship with a close look into the mobile handset industry. In this chapter, we zoom out to the macroscopic context similar to the one portrayed and analyzed in Chapter 2. While Chapter 2 primarily focused on developing efficient visualization methods and quantification schemes to help corporate decision makers understand the transformation of the business ecosystem in which they are embedded, this chapter proposes a computational framework that focuses on making inferences and developing ecosystem models in a data-driven way. If the methods in Chapter 2 are about a system that enhances the understanding on the as-is of the surrounding ecosystem transformation, the methods in this chapter are about a system that envisions the underlying mechanisms and the to-be state of the enterprises (Rouse, 2005; Basole et al., 2013b).

Today, business and innovation activities are increasingly embedded in the global network of organizations and people. Complexity that stems from this network structure hinders corporate decision makers' sight and understanding of the surrounding network environments. One source of complexity is the limited visibility into the network. Surveying the partners or suppliers that have direct relationships with the focal firm is relatively easy, compared to being aware of the partners of the direct partners. For instance, the disastrous flooding in Thailand in 2011 disturbed the global hard drive industry for years. Not to mention those hard drive manufacturers having factories in Thailand, all companies using storage devices across industries were inevitably affected by the disaster. Vigilance on the status and activities of indirect partners as well as direct partners is required in the face of a variety of risks. Recent advances in visualization help disentangle the complexity and improve visibility into the network structure (Basole and Bellamy, 2014; Park and Basole, 2015).

Another source of complexity arises due to the increased variety of modes of interdependence among nodes in the network. The fact that there are typically so many independent business entities that interact in multiple, and often conflicting, ways is an enormous source of complexity (Rouse, 2000, 2008). This may result in many types of poorly understood and poorly managed interactions. For example, Samsung Electronics supplies memory semiconductor to Apple. At the same time, their flagship mobile handsets compete head-to-head in the consumer electronics market. Even worse, these relationships evolve over time rather rapidly. Facing the complex modes of interdependence and the rapidly changing business environment, the ecosystem perspective has become a prevailing view for business intelligence (Moore, 1997; Iansiti and Richards, 2006). Recent studies have addressed the challenges from network complexity by adopting and applying visualization principles extensively (Basole, 2009). Chapter 2 also contributes to the decision-making literature in an attempt to cope with complexity using visualization. Understanding and even anticipating structural changes of the surrounding ecosystem is particularly important for firm innovation (Bellamy et al., 2014).

While the visualization approach helps decision makers by providing a visual mental model of complex ecosystems, simulation is another approach to mitigate unintended negative consequences of decision-making in a complex environment. Park et al. (2012) demonstrate that simulations can help decision makers deal with the complexity by enabling timely exploration of likely outcomes of decisions before deploying them. Moreover, if simulation methods are informed by data mining methods leveraging abundant data sources, such a computational framework can support evidence-based decision-making practices.

In this chapter, we propose a computational framework incorporating inference and prediction capabilities using both data mining and simulation approaches. To abstract and infer data-driven models of relationship formation behavior of firms, we interpret firm strategy as a sequence of decisions (Basole et al., 2015a) and we implement a sequence-mining engine adapted from Hilton et al. (2015). Based on the identified strategy clusters, we build an agent-based simulation model that investigates how organizational learning impacts the structural evolution of the business ecosystem. In addition to the interfirm alliances data used in Chapter 2, we collect mergers and acquisitions (M&A) data to enhance the coverage of interfirm activities in the ICT ecosystem.

We identify five distinct strategy profiles using the cluster analysis. We compare clustered profiles against the traditional standard industry classification (SIC) scheme. We find that there are significant crossovers between the data-driven classification and the industry segments based on the SIC codes, which suggests that companies in the same industry segment exhibit diverse behavioral patterns in forming relationships with other firms. Inspecting the top companies in each cluster provides face validity confirming our prior knowledge on existing large companies. The study in this chapter makes timely contributions to the decision-making and corporate strategy planning research and practice in the era of data abundance by demonstrating and providing a methodology that leverages the power of observational data.

The rest of the chapter unfolds as follows. Section 6.2 reviews the methodological literature on cluster analysis and organizational simulation. Section 6.3 describes our data sources and presents our analysis methods. Section 6.4 reports our findings from clustering and simulation results. Section 6.5 discusses implications of our findings and Section 6.6 concludes the chapter and suggests directions for future work extending this chapter.

6.2 Literature Review

6.2.1 Clustering and Sequence Mining

Cluster analysis has been an integral method used in many fields including including sociology (Zachary, 1977), bioinformatics (Li and Godzik, 2006; Huang et al., 2010; Fu et al., 2012), physics (Girvan and Newman, 2002), and applied mathematics (Porter et al., 2009) to name only a few. The importance of cluster analysis is ever-increasing because of two main reasons. One is the proliferation of network data thanks to advancement in social network services. The network science is gaining significant attention in academic circles from natural sciences to social sciences (Barabási, 2003; Watts, 2004) alike. The other reason is that the amount and variety of data are getting bigger and wider, so it becomes harder and more critical to make generalizable insights out of "big data" than ever. Cluster analysis provides a succinct summary of groupings of large data that is beyond usual human cognition.

Cluster analysis is an unsupervised task of assigning a set of objects into homogeneous groups. Depending on the number of groups in demand, the nature of clustering tasks can be divided into the following two kinds of problems. In the first case, the number of clusters is known when clustering is carried out. Graph partitioning is one line of research that fits this type of clustering. One of the most well known examples of such tasks that arise in computer science is assigning to multiple processors a number of interdependent tasks represented as a graph (Aguilar and Gelenbe, 1997). Since the number of processors is likely fixed and known, a clustering algorithm that cannot consider the predefined number of clusters is of little practical use in this context. Community structure detection, on the other hand, pursues a slightly different goal in the task of clustering. In this setting, the number of communities is unknown beforehand. Not only grouping nodes precisely but also determining the number of meaningful clusters latent in the graph structure is of great importance in this class of problems. Social network analysis falls into this category (Newman, 2006).

Indeed, many clustering algorithms have been proposed in the data mining society. Among them is hierarchical clustering, k-means clustering, distribution-based clustering (Ester et al., 1996), and so forth. They are commonly based on the similarities or closeness among nodes. Han et al. (2011) and Gan et al. (2007) provide a thorough survey on details of the algorithms. Conceptually, in view of the number of clusters in demand, two approaches are possible in cluster analysis: agglomerative and divisive methods. Agglomerative methods start from grouping nodes with the highest similarity and repeat the process with recalculated similarities among groups and nodes. The agglomerative approach is more intuitive than the divisive approach, so it was developed earlier and has been widely used. Agglomerative hierarchical clustering is a representative example of this approach when the true number of clusters is unknown. This approach needs to be followed by an additional critical step that involves a decision criterion for the optimal number of clusters (Jung et al., 2003). k-means clustering groups nodes in a similar way with a predefined number of centroids. In contrast, divisive methods—possessing inherent rules for the optimal number of clusters—repeat cutting the network successively until no subdivision of the network yields gain. One of the methods in this avenue is modularity-based clustering proposed by Newman (2006). Modularity measures how precise a division of the network is against a graph with edges placed at random and has played an essential role in detecting community structures in networks. One drawback of this method is that the random modularity measure employs a fixed global model, which assumes that each node can be linked to any other nodes of the network whether they are large or small regardless of the geometric structure of the network. Thus, it cannot adjust the level of resolution or the scale on which the modularity measure relies. Although taking less inputs from users is a desirable property of an algorithm in general (Hilton et al., 2015), there can be situations where users want to adjust a certain set of intuitive parameters. Park and Lee (2014) is a clustering algorithm based on information-theoretic dependence measure that possesses flexibility by taking in the scope parameter that adjusts the level of scale for parsing the geometric structure of the network.

The methods reviewed so far assume static network data that does not incorporate the time dimension. In practice, there is a growing need for clustering a sequence of data points. An exemplary case is genome sequencing in bioinformatics. Since the human genome project (Collins, 1998; Collins et al., 2003), a series of sequence clustering algorithms was developed that specialized in identifying common sequences and comparing them against a library of sequences (Li and Godzik, 2006; Huang et al., 2010; Fu et al., 2012). Clustering sequences of events has been an important problem in the business domain as well. For instance, customer purchase history is a good example of sequence data. Agrawal and Srikant (1995) developed a sequence clustering algorithm that can be used to identify frequently occurring transaction patterns and Pei et al. (2001); Mortazavi-Asl et al. (2004) improved the efficiency of the algorithm. These sequence clustering methods focus on finding frequent subsequences largely ignoring the underlying transition model. Hilton et al. (2015) developed a model-based clustering method that estimates transition matrix and inter-arrival time matrix. They applied the method to a large patient visits dataset and successfully classify five profiles of patients based on their event sequences. Their method allows characterization of each profile using estimated transition and inter-arrival time matrices.

While sequence clustering is actively used in many fields, the literature on business ecosystem and interfirm alliance mostly relies on predefined firm classification schemes such as the SIC code. Although the SIC scheme provides a hierarchical classification of firms based on industry that they are operating in, it fails to capture specific firm behavior. For example, it is possible that firms in software industry exhibit similar behavior in alliance formation with firms in digital hardware manufacturing, but these two industries are distant to each other in the SIC scheme. Considering interfirm alliance sequence can be conceptualized as gene of the company[1], we can complement the standard way to cluster firm strategy by applying established sequence clustering methods to the business ecosystem context. This chapter primarily adopts Hilton et al. (2015) and apply their method to the business ecosystem formation context.

6.2.2 Organizational Simulation

Modeling organizations as a collection of agents has a long history in the complex adaptive systems research (Prietula et al., 1998; Rouse and Boff, 2005). This approach has been widely accepted in various fields including organization science (March, 1991; Anderson, 1999; Burton, 2003; Burton and Obel, 2011) and operations management (Nilsson and Darley, 2006; Pathak et al., 2007; Nair et al., 2009). In a complex adaptive system, even when agents are prescribed with simple behavioral rules that only consider local areas around, we can observe certain emergent macro patterns in the system level. By virtue of enhanced computing power these days, this agent-based modeling combined with computer simulation has generated many exciting examples of system-level patterns from minimal rules governing individual behavior.

Computer simulation has long been used to emulate the behavior of physics-based systems (Gould and Tobochnik, 1995). Ranging from molecular biology (Levitt, 1976; Dror et al., 2012) to astronomical systems (Bertschinger, 1998), simulation provides a cost-efficient way to predict the future state of a system given a certain set of inputs. In addition to cost efficiency, simulation is often the only feasible way for systems that do not lend themselves well to analytical solutions or field experiments. Human

[1] http://entsci.gatech.edu/genome/

systems with little or limited adaptive agent behavior also greatly benefit from simulation methods. Manufacturing systems and queueing systems are good examples and simulation is widely used and accepted in modeling such systems. However, organizational simulation became a promising feasible method for modeling social and behavioral phenomena not long ago. March (1991) is a groundbreaking study that uses agent-based simulation to elicit the trade-off between exploration and exploitation. Following him, simulation methods become widely adopted in organization science (Anderson, 1999; Burton, 2003; Burton and Obel, 2011). For recent studies that use organizational simulation, Kane and Alavi (2007); Rahmandad (2008); Posen and Levinthal (2012); Jain and Kogut (2014) provide excellent examples of such studies.

Organizational simulation as a research method is facing a big driver for change these days because of abundant organizational network data accumulated and available from social network services. Since March (1991), organizational simulation has mostly relied on prescriptive parametric assumptions and normative behavior of agents in setting up the experiments. A large gap emerges between normative modeling assumptions and empirical observations. To address this challenge, researchers particularly from computer science start bridging the gap by proposing simulation approaches that incorporate observational data. One class of problem that often require considering empirical observation for feeding simulation is link prediction in networks. In practice, link prediction algorithm can be used to recommend a new relationship in social network services (Liben-Nowell and Kleinberg, 2007). Leskovec et al. (2008) take one step further to propose a method to replicate a social network using a link-generating process informed by observed network data. Recent studies, Tomasello et al. (2013, 2014, 2015), apply this approach to organization and innovation management studies. Using a simulation model informed by the observed interfirm alliance network and patent data, they investigate how firm's position in a network is related to innovation output. In light of research domain and method, their studies are closest to our study in this chapter.

Our organizational simulation model is informed by the results from the clustering algorithm developed by Hilton et al. (2015). Their method estimates transition probabilities and inter-arrival times, so our simulation model is in essence to simulation continuous-time Markov chains (CTMC). Gillespie (1976) develops one of the first algorithms to simulate CTMC called the Stochastic Simulation Algorithm (SSA). The basic idea is the combination of discrete-time Markov chains (DTMC) and exponential holding times. This simulation method has been adopted for a wide range of fields including gene sequencing (McAdams and Arkin, 1997) as much as CTMC is a useful tool to model various systems. Banks et al. (2007) provide a detailed and technical review on various methods for simulating CTMC including the SSA and other variants such as CTMC incorporating jump processes.

6.3 Data and Methods

6.3.1 Data Source

Our data comes from Thomson Reuter's SDC Platinum (SDC). SDC provides curated data of interfirm alliances and M&A events by scanning various primary sources such as SEC filings. It is the standard data source used for interfirm alliance research (Schilling, 2009). It uses CUSIP as the primary company identifier.

The SDC alliance data contains primary SIC code, location (city, state, country), business description of participating companies as well as announced date. Most of the alliances are between two companies, while some alliances involve more than two participants. The joint venture is a special type of alliances. Each alliance is marked whether or not it is a joint venture activity. Along with the joint venture flag, many other binary flags indicate subtype of the alliance. The subtypes include strategic alliance, R&D alliance, marketing alliance, technology transfer alliance, manufacturing and supply alliance, and licensing alliance.

The M&A database consists of two parts. One part contains domestic activities in the U.S., while the other part records international M&A activities. Each M&A record lists acquiring firm and target firm. Other data fields include primary SIC code, location, business description for both firms. Regarding the acquisition activity, SDC provides the announced date and the percentage shares acquired after the transaction. Following Jakobsen and Meyer (2008), we break down the M&A activities into three groups based on the shares involved in the transaction. Full acquisition is defined when 95% or more shares were acquired after the transaction. Transactions involving less than 10% of shares are classified as portfolio investment activities. Other transactions that fall in between the two thresholds are defined as partial acquisition.

We filter companies by primary SIC code to retrieve companies in the ICT ecosystem. We use the 58 SIC codes listed in Table 1 in Chapter 2. We follow the same industry segment classification used in Chapter 2 classifying 58 SIC codes into 5 segments: (1) hardware components, (2) hardware equipment, (3) software, (4) telecommunications, and (5) media. In order to observe longitudinal behavior of companies in forming relationship, we retrieve 25-year long data spanning from 1989 to 2014. This filtering criteria produced 179,021 total events that consist of 69,026 alliances and 109,995 M&A activities. We identify 116,993 unique firms from this merged dataset.

6.3.2 Sample and Variables

The population data contains 116,993 unique companies involved in 179,021 events, which means that on average a firm has less than two (1.53) relationship-forming activities. The majority of companies in our dataset appears only once in either alliance or M&A event. Since we are interested in the sequence of activities of companies in the ecosystem, we further narrow down our sample to include those having appeared in at least five different events. This leaves us with 6,392 companies in the final sample.

Table 30 shows the summary statistics of our sample. On average, a company forms 13.07 relationships with others. 75% of those relationships are either alliance or full acquisition. Partial acquisition and joint venture account for 15% and 7%, respectively. We rarely observe pure portfolio investment activities (3%). Among alliance or joint venture events, most of them are strategic alliances. Other subtypes of alliance and joint venture are evenly distributed between 30-40%. About 35% and 38% of interfirm relationships are cross-border and cross-segment. We define cross-border activities as at least one participating firm has a different nationality to another. Cross-segment activities are similarly defined depending on segment membership of participating companies. Formulas for computing the ratios are as follows.

$$r_{\text{type},i} = \frac{N_i}{\sum_{j\in\{\text{AL,JV,FA,PA,IV}\}} N_j}, \qquad \forall i \in \{\text{AL,JV,FA,PA,IV}\} \tag{21}$$

$$r_{\text{subtype},i} = \frac{N_i}{N_{\text{AL}} + N_{\text{JV}}}, \qquad \forall i \in \{\text{ST,RD,MK,TT,MF,LS}\} \tag{22}$$

Equation (21) is the formula for the main relationship type ratios and Equation (22) is for the subtype ratios specifically for alliances and joint ventures. See Table 30 for the two-alphabet acronym for each type and subtype.

6.3.3 Clustering

Our analysis process starts with clustering firms based on their relationship formation behavior. We directly adopt the model-based clustering method proposed by Hilton et al. (2015). The method uses a Markov renewal process (MRP) to model the sequence of events. Each event belongs to a certain type and a sequence is considered one realization of the underlying process. Using the MRP framework, their algorithm aims to estimate transition probability and inter-arrival time matrices as well as bundle observations into homogeneous groups.

Table 30: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Total Frequency	6,392	13.07	27.81	5	1,044
Ratio of Alliance (AL)	6,392	0.30	0.29	0	1
Ratio of Joint Venture (JV)	6,392	0.07	0.14	0	1
Ratio of Full Acquisition (FA)	6,392	0.45	0.32	0	1
Ratio of Partial Acquisition (PA)	6,392	0.15	0.21	0	1
Ratio of Investment (IV)	6,392	0.03	0.07	0	0.83
Ratio of Strategy (ST) Alliance or JV	6,392	0.83	0.29	0	1
Ratio of R&D (RD) Alliance or JV	6,392	0.32	0.41	0	1
Ratio of Marketing (MK) Alliance or JV	6,392	0.42	0.41	0	1
Ratio of Tech Transfer (TT) Alliance or JV	6,392	0.40	0.41	0	1
Ratio of Manufacturing (MF) Alliance or JV	6,392	0.33	0.42	0	1
Ratio of Licensing (LS) Alliance or JV	6,392	0.33	0.42	0	1
Ratio of Cross-Border Relationship (CB)	6,392	0.35	0.30	0	1
Ratio of Cross-Segment Relationship (CS)	6,392	0.38	0.29	0	1

Moreover, Hilton et al. (2015) considers the censored nature of observational sequence data. Since we observe birth and death of companies using our dataset. Nonexistence of a relationship after a certain point of time does not necessarily mean that the firm died. Thus, our sequence data is censored before and after the observation period from January 1, 1989 to December 31, 2014. To take care of this problem, their algorithm adds two additional states: left censor (LC) and right censor (RC). Before running the algorithm, we pad each sequence with LC and RC at the beginning and at the end, respectively. By definition, every sequence starts with LC and ends with RC. Since no transitions come back to LC and go out from RC, the matrices estimated by the algorithm have the structure portrayed in Figure 31.

They use maximum likelihood estimator (MLE) for each element of matrices. For the transition probability from state s_i to state s_j, the MLE is the number of transitions from s_i to s_j divided by the total number of transitions out of s_i. For the inter-arrival time from s_i to s_j, the MLE is the sum of observed transition times from s_i to s_j divided by the total number of transitions from s_i to s_j.

They use the Bayesian information criterion (BIC) for model selection. At each

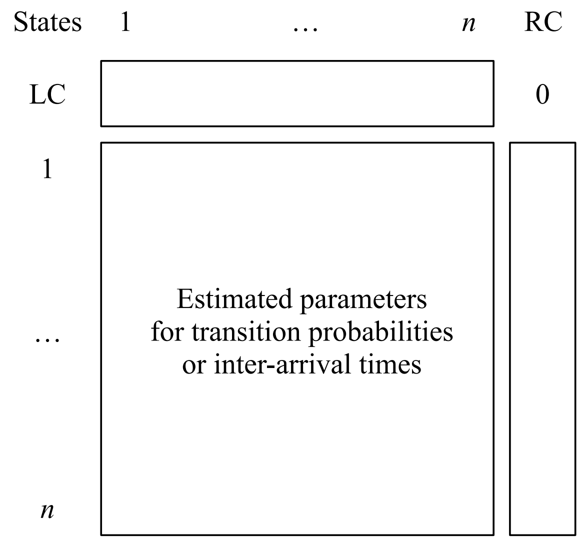


Figure 31: Matrix Structure for Parameter Estimation

iteration, further division is performed only if such a division increases BIC. BIC shown in Equation (23) represents the trade-off between better fitting the data and complexity of the model to avoid over-fitting problems. The equation for BIC is as follows.

$$\mathrm{BIC}(M) = \underbrace{l(M)}_{\text{Model fit}} - \underbrace{b \cdot |M| \cdot \log(R)/2}_{\text{Penalty for model complexity}} \tag{23}$$

where M is the model under evaluation and R is the number of firms. We introduce one new constant parameter b to adjust for the different size of the state space for the following reason. We construct the state space by taking the Cartesian product of three dimensions: primary type of relationship, subtype of certain relationship, cross-border/within-border relationship, and cross-segment/within-segment relationship. We have five primary types of relationship (alliance, joint venture, full acquisition, partial acquisition, and portfolio investment) and alliance and joint venture relationship types have eight subtypes (strategy, R&D, marketing, technology transfer, manufacturing, licensing, multiple subtypes combined, and unspecified). As a result, the size of our state space is 76 ($= ((2 \times 8) + 3) \times 2 \times 2$). It is about ten times greater than the number of states in Hilton et al. (2015) that has six states. Since the number of parameters to be estimated is proportional to the square of the number of states, the model size is about 100 times greater than Hilton et al. (2015). This results in over-penalization for model size because of the penalty term is proportional to the model size as shown in Equation (23). Except for this minor adjustment, our clustering method precisely follows Hilton et al. (2015). In short, the clustering algorithm can be summarized as follows.

Step 1. Start with the null hypothesis that all firms belong to a single cluster. Compute MLEs for transition probability and inter-arrival time matrices. Compute the BIC_0 based on the MLEs which serves as a reference point for model selection.

Step 2. Compute potential partitions that divide the population in two based on the Kullback-Leibler (KL) distance. The KL distance quantifies the distance between two distributions. For each partition, compute the BIC_A assuming that the partition is applied. These are BIC scores for alternative hypotheses that dividing the population is a better model.

Step 3. Choose the partition that maximizes BIC. Run the expectation maximization (EM) algorithm to obtain BIC_A^*.

Step 4. If $\text{BIC}_A^* > \text{BIC}_0$, apply the partition to divide the population. Repeat this procedure for each clustered population until no further divisions can be made.

Once the clustering algorithm produces labels for each firm, we run multinomial logistic regressions to identify key factors that characterize each cluster. The response variable is cluster membership. We use the largest cluster as the baseline group or the pivot, so the regression model is as follows.

$$\ln \frac{Pr(Y_i = k)}{Pr(Y_i = K)} = \alpha_k + \beta_k \mathbf{X}_i + \varepsilon_i \tag{24}$$

where Y_i is the cluster membership of firm i, k is the focal cluster number, K is the baseline cluster number, and **X** stands for the matrix containing the explanatory variables.

6.3.4 Simulation

After we estimate transition probability and inter-arrival time matrices for each cluster, we simulate the ICT ecosystem formation process as CTMC. We modify the SSA laid out in Banks et al. (2007) to accommodate the organizational learning perspective we are interested in. In simulation, each firm is populated with one of the clustered profiles. As the simulation progresses, each firm learns from prominent benchmark firms based on network centrality measures at different speed. In short, our simulation procedure can be summarized as follows.

Step 1. Populate given number of firms (n) and assign a cluster profile, rate of relationship formation, industry segment, and geographic region from empirical joint distribution. Set simulation time $t = 0$.

Step 2. Initialize all firms starting at the LC state. Draw τ_i from the exponential distribution with rate λ_i for all i. Determine the destination state from the transition probability matrix. The event partner is chosen based on segment and geographic region.

Step 3. Keep updating the new time $t = t + 1$ until there exist some firms whose $\tau_i < t$. For those firms, make the transition and draw ξ_i from exponential distribution with rate λ_i. Update $\tau_i = \tau_i + \xi_i$.

Step 4. For every time tick, each firm learns from the benchmark chosen from the predefined rule (e.g., firms with high degree) at the predefined speed. Learning only occurs when the benchmark firm has a higher rate than the focal firm.

Step 5. Repeat Steps 3-4 until $t \geq t_{\text{stop}}$ or all firms reach the absorbing state, the RC state.

Each simulation run is populated with 1,000 agents. We run the simulation 100 times for each combination of input parameters on organizational learning and take the average to summarize the outcome. Each replication run simulates the ICT ecosystem for 9,125 days (= 365 days $\times$ 25 years).

We set up simulation experiments along with three varying parameter dimensions. The first dimension is the composition of agents based on the clustered profiles. Since we identified five behavioral profiles, the composition is a vector of five elements that sum to one. We start with the original profile composition and vary the composition to see if what happens when the ICT ecosystem consists of only a single profile. We can then associate the identified characteristic of clustered profiles with macro patterns of the ecosystem. The second parameter dimension is the way firms choose their benchmark to learn from. We start with the most straightforward benchmark criteria: the prolificity of firms. In other words, firms mimic behavior from those that have the most interfirm activities in the ecosystem. For each simulation time step, the simulation sort all firms based on the number of their established interfirm relationships in descending order. The parameter governs the cutoff threshold for the list. For example, if the threshold is set to be 0.1, it means each firm benchmarks from a company in the top 10% most prolific companies list. If it is set to be 0, then no firms make adjustments in their rate and transition probabilities. The third parameter dimension is the organizational learning speed. We assume that each firm learns from the chosen benchmark in a linear way every time tick. The baseline speed of learning is the reciprocal of the total time span (=1/9125) multiplied by the difference between the focal firm and the benchmark firm. The learning speed parameter is a multiplier to the baseline speed. Firms learn two elements from the benchmark: interfirm relationship formation rate and transition probability matrix. Thus, firms become homogenized over time through the mimicry mechanism specified in this simulation. Table 31 summarizes our parameter space.

Table 31: Simulation Experiment Setup

Parameters	Values
Profile Composition	{Original Composition, Profile 1 Only, Profile 2 Only, Profile 3 Only, Profile 4 Only, Profile 5 Only}
Learning Benchmark Selection Cutoff Threshold	{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1}
Learning Speed	{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1}

6.4 Results

6.4.1 Clustering

We identify five clusters based on transition behavior. The clustering algorithm we use is a iterative divisive method, so clusters emerge as a tree structure. Figure 32 illustrates the hierarchical structure identified by the clustering process. As explained earlier, the algorithm starts with the null hypothesis that puts all firms into a single cluster. Each cluster node is divided in two iteratively until it cannot be broken down further.

Five final clusters are denoted in larger font at the bottom of Figure 32. Each cluster is labeled from 1 through 5. One thing to note is that the identified clusters contain firms rather disproportionately than evenly. Cluster 1 includes more than 75% of all firms in our sample, while Cluster 4 has only 1%. Note that this tree represents the number of firms assigned to each cluster before running the EM algorithm. The final cluster assignment has slightly more even distribution across five profiles.

Before abstracting defining features and characteristics of the identified clusters, we survey the top companies in each cluster. Table 32 shows the top 10 companies for each of five clusters. The number in parenthesis next to the company name means the number of alliances or M&A relationship that the company formed in our sampling time frame between 1989 and 2014. Cluster 1 contains some of the most prolific companies in relationship formation, but the overall propensity of all

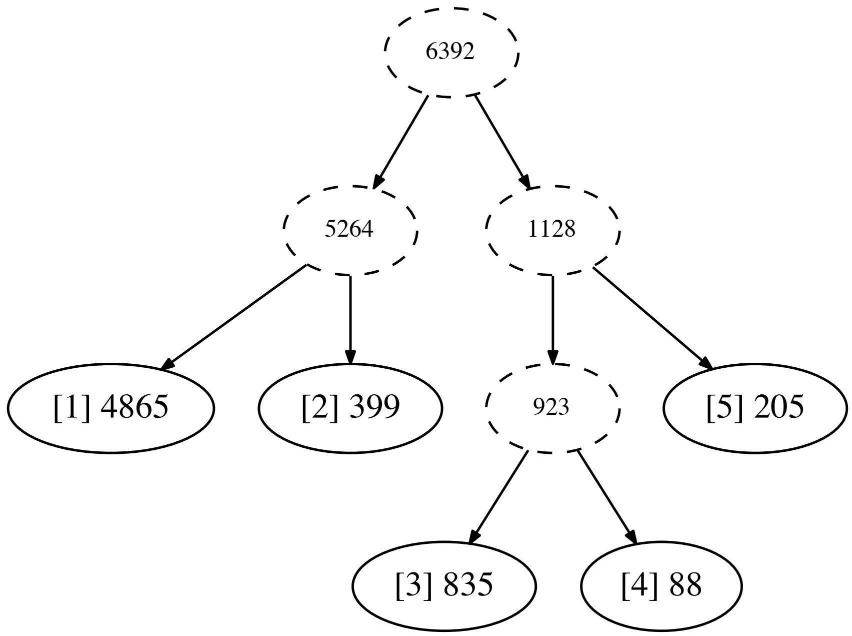


Figure 32: Hierarchical Structure of Clustering Process

companies in the cluster is about 11.69 relations during the tenure, which is not particularly high. On the contrary, companies in Cluster 5 formed about four times more relations than those in Cluster 1 on average. We can infer that Cluster 5 consists of a focused set of highly active companies exclusively, while Cluster 1 is rather generic. Looking through the lists, we can also spot association between identified clusters and industry segments. 7 out of top 10 companies in Cluster 2 have "media", "advertising", "communications", or "broadcasting" in their names, which suggests Cluster 2 covers many media companies. Cluster 3 contains renowned software or information service companies such as Google, Yahoo, America Online, and Adobe. We do not recognize notable companies in the top 10 list of Cluster 4 except for Sharp. Lastly, Cluster 5 includes prominent hardware manufacturers such as Cisco, Samsung, Nokia, and Compaq.

Table 32: Top 10 Companies for Each Cluster

Rank	Cluster 1 ($N = 4,555$)	Cluster 2 ($N = 431$)	Cluster 3 ($N = 1,053$)
1	IBM Corp (1,044)	21st Century Media Newspaper (32)	Texas Instruments Inc (240)
2	Microsoft Corp (838)	LookSmart Ltd (24)	America Online Inc (178)
3	Hewlett Packard Co (601)	Perficient Inc (23)	Yahoo! Inc (169)
4	Motorola Solutions Inc (459)	Transcontinental Media GP (20)	Google Inc (162)
5	Intel Corp (362)	Lamar Advertising Co (19)	Thomson Reuters Corp (143)
6	AT&T Corp (355)	Ebix Inc (18)	SAP AG (139)
7	Siemens AG (344)	Cox Radio Inc (17)	Adobe Systems Inc (136)
8	Hitachi Ltd (315)	Arch Communications Group Inc (17)	Unisys Corp (132)
9	Toshiba Corp (299)	Davel Communications Inc (16)	Computer Sciences Corp (123)
10	Digital Equipment Corp (289)	Nexstar Broadcasting Group Inc (16)	Symantec Corp (108)
Avg. Freq.	11.69 (27.85)	6.84 (2.96)	15.52 (19.60)

Rank	Cluster 4 ($N = 108$)	Cluster 5 ($N = 245$)
1	Sharp Corp (83)	Cisco Systems Inc (361)
2	SFX Broadcasting Inc (28)	NEC Corp (354)
3	American Radio Systems Corp (18)	Sun Microsystems Inc (318)
4	TsentrTelekom (18)	Oracle Corp (234)
5	Monradio Srl (16)	Novell Inc (233)
6	Pulitzer Newspapers Inc (14)	Samsung Electronics Co Ltd (223)
7	InfoCure Corp (13)	Telefonaktiebolaget LM (201)
8	Triathlon Broadcasting Co (13)	CA Inc (189)
9	Capstar Broadcasting Partners (13)	Nokia Oyj (174)
10	EZ Communications Inc (12)	Compaq Computer Corp (168)
Avg. Freq.	7.96 (8.05)	41.36 (55.96)

In Chapter 2, we used industry segments to categorize firms operating in different domains. The clusters we identify in this chapter are based on observed link formation behavior, thus our clustering results can complement the traditional industry classification scheme. The previous analysis about the similarity between clusters and segments is based on qualitative assessments of the top companies in each cluster. The next step is to consider all companies to see how our clustering results are correlated with industry segments. Table 33 shows the cross-tabulation results between cluster assignments and industry segments. Percentages are computed by column so that each column sum equals to 100%. In order to find which segment is over- or under-represented in each cluster, we need to make row-wise comparisons of the percentage values.

Inspecting Table 33 mainly confirms the insights gained from the analysis using top companies for each cluster. Media companies have a strong presence in Cluster 2. 26.91% of firms in Cluster 2 are in the media segment, while media companies take up only 20.04% overall. Similarly, Cluster 3 overly represents software companies and Cluster 5 has excessive hardware equipment manufacturing enterprises. In addition, the cross-tabulation reveals the character of Cluster 4. We know from the clustering tree diagram (Figure 32) that Cluster 4 branches out from Cluster 3. Its contents, however, represent a significant amount of media companies excessively above the average. Cluster 1 is quite generic in that it has a similar composition of segments compared with the average distribution. In sum, there are some indications that companies in the same segment form interfirm relationship in a similar way, but there are considerable numbers of crossovers across different segments.

Table 33: Cross Tabulation between Clusters and Segments

	Cluster Number					
Segment	1	2	3	4	5	Total
1 Hardware Components	475 10.43%	20 4.64%	29 2.75%	1 0.93%	15 6.12%	540 8.45%
2 Hardware Equipment	678 14.88%	11 2.55%	45 4.27%	3 2.78%	41 16.73%	778 12.17%
3 Software	1,995 43.80%	224 51.97%	663 62.96%	44 40.74%	71 28.98%	2,997 46.89%
4 Telecommunications	505 11.09%	60 13.92%	140 13.30%	21 19.44%	70 28.57%	796 12.45%
5 Media and Others	902 19.80%	116 26.91%	176 16.71%	39 36.11%	48 19.59%	1,281 20.04%
Total	4,555	431	1,053	108	245	6,392

We then move on to characterize clusters in a more general term. Since our clustering algorithm is based on the transition patterns, it is imperative to examine the transition diagram in order to characterize each cluster profile. One practical problem to visualize the transition diagrams is that we have 78 states in total including

LC and RC states, which is significantly greater than the number of states visualized in Hilton et al. (2015). Although we have 25 years of data, estimating transitions between 78 states may pose several technical challenges. We can possibly reduce the state space by ignoring the subtypes of alliance and joint venture. However, the trade-off is that we also lose additional information for inferring firm behavior if we drop the subtypes. In this chapter, we decide to utilize maximal information by proceeding with 78 states.

The inflation of the state space is largely due to the Cartesian product of different types of states: main link type, subtype, and cross-border/cross-segment. Decomposing a transition matrix to reduce the number of states is possible only when the Markov chain is lumpable (Kemeny and Snell, 1960). Since it is nearly impossible for an empirically estimated transition matrix to satisfy the lumpability condition, we take a different approach to generate the transition diagrams. Instead of decomposing the full transition matrix, we estimate smaller-size transition matrices given the clustering results. In the data level, we reduce state space and estimate the corresponding transition matrix in a similar way for the full transition matrix. As a result, we obtain three transition diagrams for each cluster profile.

Appendix Section A.1 shows all diagrams. Each diagram has two gray nodes: LC and RC. All transitions start from LC and end at RC. Line thickness is rendered based on stratification of transition probabilities. Following Hilton et al. (2015), thick lines denote probabilities greater than or equal to 0.33, normal solid lines denote probabilities greater than or equal to 0.2, and dashed lines denote probabilities greater than or equal to 0.1. We do not visualize probabilities less than 0.1 except for transitions coming out from LC or transitions going into RC. Cluster 1 joins the ICT ecosystem via either alliance or full acquisition with similar probability (40% and 31%). Full acquisition is the primary entry point for Clusters 2-4. Cluster 5 relies heavily on joint ventures to establish presence in the ICT ecosystem. We do not find significant differences in transitions across different subtypes. This is largely because M&A relationship does not have subtype information. In terms of cross-border and cross-segment relationship, Cluster 5 is the only cluster that pursues cross-boundary relationship, while all other clusters tend to anchor around within-border and within-segment relationship.

Table 34: Predictors for Cluster Membership

	Cluster = 2	Cluster = 3	Cluster = 4	Cluster = 5
(Log) Total Frequency	-1.186**	0.783**	-0.342	1.283**
	(0.190)	(0.057)	(0.343)	(0.095)
Ratio of Alliance	-5.386**	-1.147**	6.295**	-1.990**
	(1.010)	(0.250)	(1.976)	(0.441)
Ratio of Joint Venture	-12.116	-4.039**	34.262**	0.324
	(8.703)	(0.825)	(9.533)	(0.648)
Ratio of Full Acquisition	2.448**	0.367*	6.572**	-2.247**
	(0.365)	(0.185)	(1.077)	(0.419)
Ratio of Investment	-8.511**	-2.640**	-26.870**	0.365
	(2.030)	(0.738)	(9.713)	(0.792)
Ratio of Strategy Alliance or JV	1.729	0.214	23.311*	0.382
	(1.827)	(0.253)	(10.180)	(0.417)
Ratio of R&D Alliance or JV	0.229	0.353†	2.564*	1.484**
	(0.428)	(0.210)	(1.065)	(0.339)
Ratio of Marketing Alliance or JV	-0.229	-0.257†	2.105†	-0.589*
	(0.296)	(0.146)	(1.168)	(0.264)
Ratio of Tech Transfer Alliance or JV	-0.232	-0.308†	-1.953†	-1.607**
	(0.354)	(0.169)	(1.108)	(0.426)
Ratio of Manufacturing Alliance or JV	-0.041	-0.194	-0.210	-1.253**
	(0.454)	(0.177)	(0.909)	(0.369)
Ratio of Licensing Alliance or JV	0.660	0.473**	3.375*	1.265**
	(0.406)	(0.172)	(1.412)	(0.359)
Ratio of Cross Border Relationship	-7.187**	-0.946**	-10.484**	0.701**
	(0.636)	(0.137)	(2.835)	(0.251)
Ratio of Cross Segment Relationship	-1.579**	-1.364**	-1.777**	0.983**
	(0.252)	(0.165)	(0.599)	(0.307)
Constant	-0.803	-2.193**	-34.408**	-5.620**
	(1.909)	(0.298)	(10.237)	(0.464)

Note: Cluster = 1 is the base outcome. Robust standard errors are in parentheses.
†, *, ** denotes statistical significance at 10%, 5%, and 1%, respectively.

In addition to inspecting the transition diagrams, we use multinomial logistic regressions to significant factors that determines cluster assignments. Table 34 shows the regression results. As Cluster 1 is the most generic profile, we use it as the baseline. The ratio of partial acquisition and the ratio of non-specified subtype are omitted due to multicollinearity.

First of all, active and prolific companies have a higher chance to belong to Cluster 3 or 5, while firms with only a small number of interfirm relations likely belong to Cluster 2. In terms of main link types, Cluster 3 is characterized by aversion to joint ventures, while Cluster 4 is extremely geared toward joint ventures. Both Clusters 2 and 3 rely on full acquisitions with little emphasis on alliances or portfolio investments. The regression analysis also reveals the characterization on subtypes. Cluster 4 is the only cluster that focuses on strategic alliances. Clusters 4 and 5 actively engage in R&D and licensing activities. The difference between the two is marketing collaborations. Cluster 4 joins relatively more marketing alliances, while Cluster 5 does not participate much in marketing, tech transfer, or manufacturing collaboration activities. Lastly, only Cluster 5 forms cross-border and cross-segment relationship actively, which confirms the finding from examining the transition diagrams.

Table 35: Cluster Labels based on Company Description

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
manufactur (0.0236)	manufactur (0.0072)	manufactur (0.0157)	manufactur (0.0038)	telecommun (0.0053)
servic (0.0105)	llc (0.0040)	equip (0.0060)	station (0.0029)	domest (0.0039)
provid (0.0094)	louisiana (0.0032)	servic (0.0057)	found (0.0028)	cellular (0.0033)
internet (0.0076)	compani (0.0026)	found (0.0056)	also (0.0020)	fix (0.0032)
equip (0.0071)	inc (0.0024)	internet (0.0055)	base (0.0019)	cabl (0.0031)
semiconductor (0.0053)	locat (0.0024)	locat (0.0052)	solut (0.0018)	internet (0.0028)
product (0.0053)	vega (0.0023)	provid (0.0039)	compani (0.0018)	telephon (0.0027)
wholesal (0.0043)	tennesse (0.0023)	compani (0.0038)	softwar (0.0017)	manag (0.0026)
devic (0.0040)	kentucki (0.0023)	compon (0.0034)	radio (0.0016)	latin (0.0024)
found (0.0039)	nevada (0.0023)	semiconductor (0.0030)	wholesal (0.0016)	telephoni (0.0021)

6.4.2 Organizational Simulation

Followed by the clustering results, we report simulation results. We start with the variation in the composition of agents in the ICT ecosystem. Figure 33 shows the comparison of the key network metrics over the different compositions. The baseline

Table 36: Cluster Labels based on Deal Synopsis

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
form (0.0416)	form (0.0583)	manufactur (0.0122)	form (0.0198)	interest (0.0150)
inc (0.0336)	provid (0.0544)	enter (0.0079)	provid (0.0175)	us (0.0150)
agreement (0.0333)	agreement (0.0493)	agre (0.0076)	allianc (0.0167)	stake (0.0148)
unit (0.0314)	inc (0.0485)	ltd (0.0076)	strateg (0.0163)	mil (0.0141)
allianc (0.0310)	allianc (0.0480)	ventur (0.0075)	servic (0.0162)	own (0.0139)
strateg (0.0304)	servic (0.0479)	sign (0.0072)	unit (0.0155)	termin (0.0134)
market (0.0299)	strateg (0.0472)	disclos (0.0070)	inc (0.0151)	name (0.0134)
provid (0.0290)	unit (0.0463)	detail (0.0070)	agreement (0.0133)	telephon (0.0132)
term (0.0282)	term (0.0456)	joint (0.0068)	term (0.0126)	major (0.0126)
develop (0.0279)	market (0.0429)	agreement (0.0063)	corp (0.0112)	cabl (0.0124)

group is the original composition identified by the clustering algorithm (Cluster 1: 76%, Cluster 2: 6%, Cluster 3: 13%, Cluster 4: 1%, Cluster 5: 3%). Each subsequent bar labeled as Profile 1 through 5 shows the case where the entire ecosystem is composed of companies that belong to the particular cluster. This way, we can validate whether the simulation model works as intended by examining the results of each case agree with our observations on the clustering results. The top-left chart shows the average degrees of the simulated ecosystems. Since the average degree is a measure of the propensity for forming relationships, this chart exhibits the same pattern we can see in the average number of interfirm relationships for each cluster reported in Table 32. The top-right chart shows the average clustering coefficient. Despite the small numbers of relationships, ecosystems simulated solely from Profiles 2 and 4 exhibit high tendency to form cliques. However, the small world quotient (average clustering coefficient divided by average shortest path length) shown in the bottom-left chart presents a slightly different story. Profile 5 is the most small-world-like network and immediately followed by Profile 4. Considering that companies in Profile 4 do not form many relationships, their relationships self-organize into a small world network. The last chart in the bottom-right corner shows the average ratio of cross-border-cross-segment relationship. It displays a similar trend of the average degree chart, while Profile 1 has a relatively high ratio of cross-boundary activities and Profile 2 has a relatively low ratio. The relationships formed in the simulated ecosystem containing only Profile 2 companies are mostly (> 95%) within-border or within-segment activities.

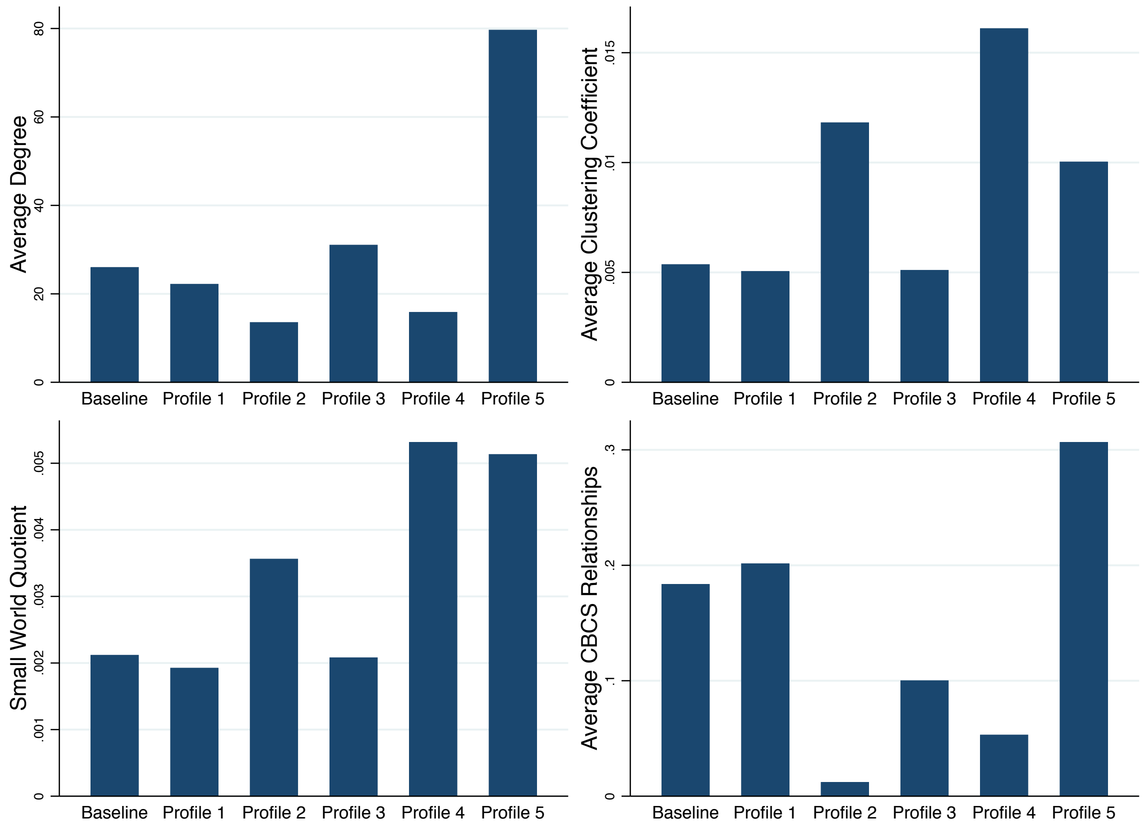


Figure 33: Simulation Results with Ecosystem Composition Varied

Next, we move on to the benchmark selection criteria parameter. Figure 34 show total number of interfirm relationships, average degree, average clustering coefficient, and average path length for the simulation ICT ecosystem on varying benchmark ranges. The thick solid line is the average value from 100 replications and the dash lines denote 95% confidence interval. The benchmark range means the cutoff ratio for selecting a benchmark for each firm. For example, if the benchmark range is 0.1, each firm learns from the benchmark chosen randomly from the top 10% prolific firms. The learning speed is fixed at the constant ratio 1/9125 of the difference between the focal firm and the benchmark firm so that it takes all 25 years for the focal firm to catch up the benchmark firm. Firms learn both the rate of relationship formation and the transition probabilities from the selected benchmark firm.

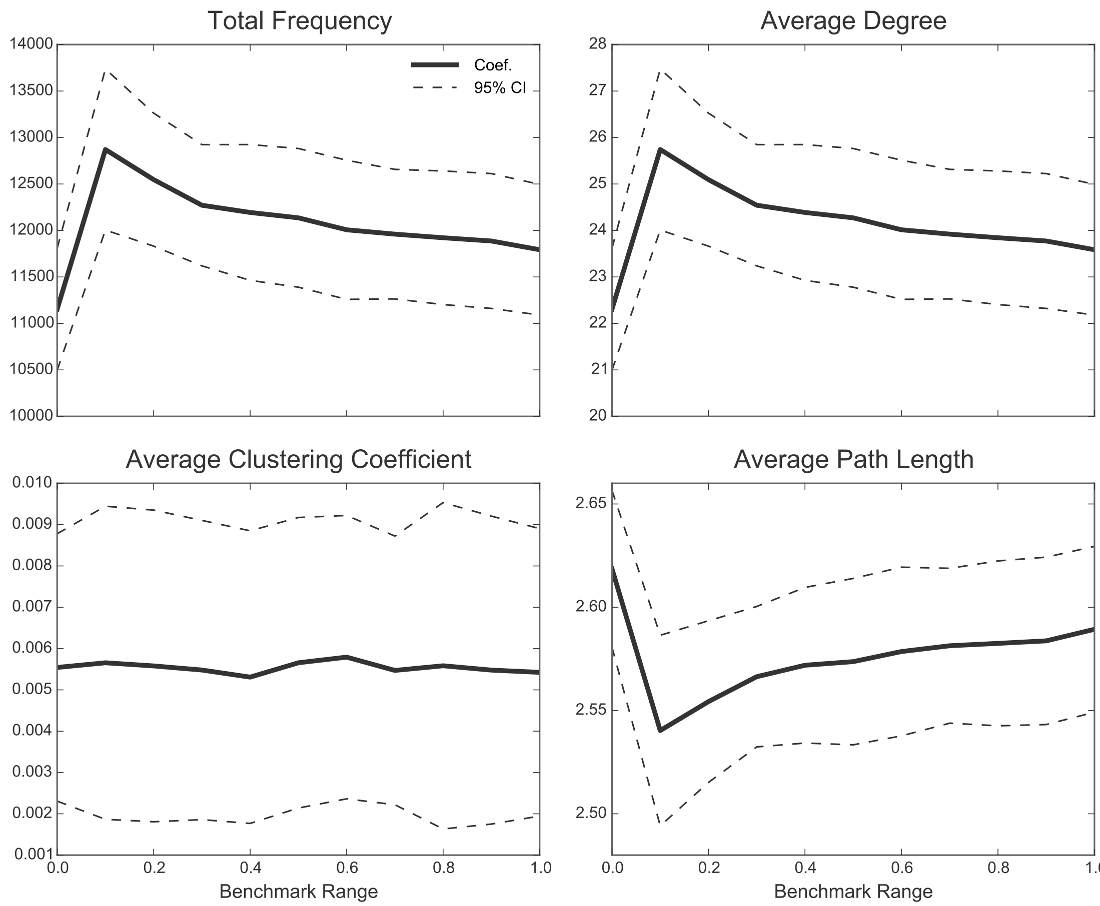


Figure 34: Simulation Results with Benchmark Range Varied

We find that the total frequency of interfirm relationships and the average degree significantly increase as the benchmark range moves from 0 to 0.1. Note that, when the benchmark range is 0, it means that no firms learn from each other. Instead, they form relationships based on their characteristics drawn from initialization. Thus, the simulated ICT ecosystem becomes dense when firms are actively benchmarking the interfirm activities of the top companies. However, as the scope of benchmark becomes wider, the density decreases as it is less likely the benchmark target company is highly prolific. As a result, the average path length of the simulated ecosystem shows an inverse pattern to the average degree chart. On the other hand, the average clustering coefficient does not seem affected by the varying benchmark range. Since a measure of small world network is the average clustering coefficient divided by the average shortest path length, it suggests that the ecosystem becomes more small-world-like when constituent firms mimic the top benchmark firms. We do not find significant differences in relationship types over this parameter space.

Lastly, we report the simulation results with the learning speed parameters varied. Figure 35 shows the same ecosystem-level network metrics to the previous figure. The learning speed of 0 means that firms do not learn from each other and the learning speed of 1 means that every firm learns from the chosen benchmark at the full speed of 1/9125. As each firm's learning speed increases, the total number of relationships and the average degree increase as we can expect from the formulation. However, the increase is not as drastic as the case where we vary benchmark selection range parameters. The average clustering coefficient is insensitive to parameter variation as before and the average path length chart shows an inverted pattern of the average degree chart similar to the previous figure. In this case, we do not find statistically significant patterns in the proportion of different types of alliances and M&A activities.

An interesting finding arises from another measure. Figure 36 shows the time to saturation against the learning speed parameters. The time to saturation is a measure of how long it takes until each simulation run has all agents arriving at the absorbing state, RC. Once an agent reaches RC, it no longer forms interfirm relationships because RC by definition stands for the right edge of the observational time frame. Our simulation stops after 25 years of simulation time steps or all firms are in the RC state. Therefore, the mean value of the simulation time window is around 9,125 and it slightly decreases as firms learn faster from each other. However, increase in standard deviation or uncertainty of saturation time is rather unexpected. It suggests that as firms speed up their learning process, the ecosystem as a collective body arrives at the final state very quickly in some cases. In other words, early termination cases

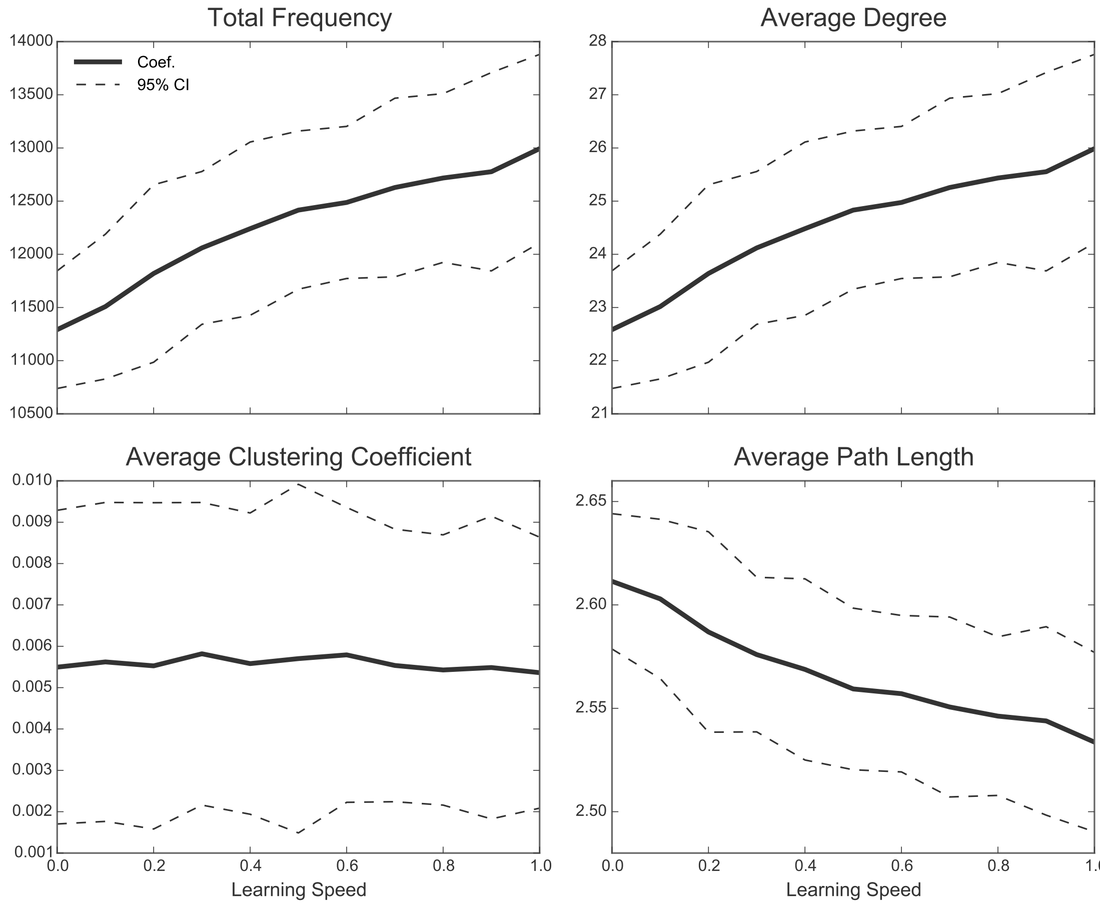


Figure 35: Simulation Results with Learning Speed Varied

occur much more frequently than the baseline model without organizational learning.

6.5 Discussions

When reporting the clustering results, we find that some companies belong to a cluster that primarily contains companies in other industry segments. For example, Texas Instruments belongs to Cluster 3, but the cluster contains many software or Internet companies such as Google and Yahoo. It is an exception in this list of top Cluster 3 companies. This type of observations leads us to formulate a hypothesis that the way Texas Instruments forms relationship follows the patterns that most software companies do. It may indicate that Texas Instruments is trying to embed itself into software-focused surrounding network. In a similar way, we can look up

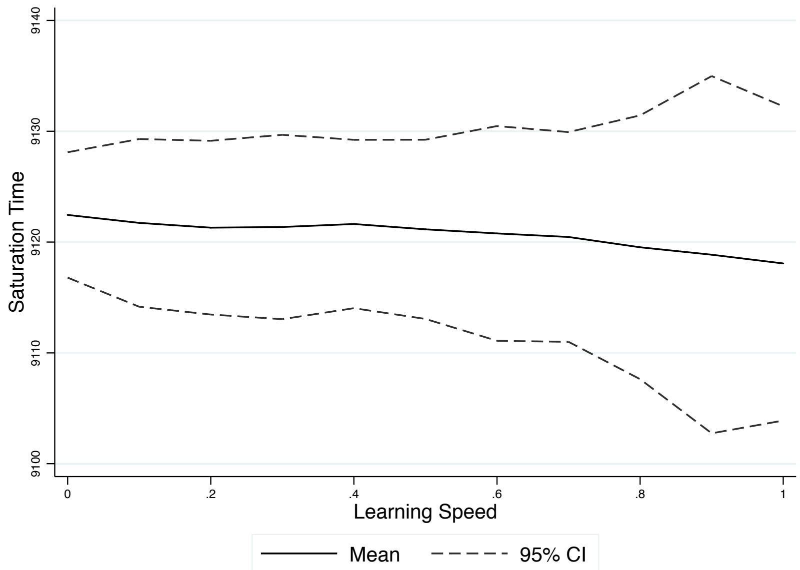


Figure 36: Time to Saturate with Learning Speed Varied

other companies of interest in the clustering results and formulate hypotheses about those companies around their relationship formation behavioral patterns.

To date, the SIC codes serve as a method to categorize companies based on the industry in which they are operating. This type of inference informed by data mining methods shown in this chapter can complement the existing classification of firms and shed light on how we can derive firm types in a data-driven way. This novel way of grouping firms based on their behavior is particularly important when the industry boundaries are blurred. Chapter 2 previously shows that the ICT ecosystem already contains a significant amount of cross-segment alliances, which characterizes convergence of the ecosystem. As traditional industry boundaries fade away, it is increasingly important to complement the SIC codes relying on the hierarchical structure of industries with methods that accommodate emergent categorizations derived from the data.

For the simulation study in this chapter, we can further make several refinements. First, we can sophisticate the benchmark selection criteria. In this chapter, the benchmark is chosen based on degree centrality. But, there are different measures that gauge the prominence or importance of a node in a network such as betweenness centrality or eigenvector centrality. For instance, betweenness centrality measure captures structural holes bridging different parts of a network and eigenvector centrality highlights highly influential nodes in a network. We can build in different objectives for each firm and each firm chooses a benchmark depending on the given objective—whether it wants to become a gatekeeper or a highly influential player.

Learning speed is another dimension we can further refine. The current model applies a uniform learning rate to all companies in the simulation. Since companies have different capabilities and resources to adapt to the changing environment or transform into the to-be state, we can build in heterogeneous learning speed for companies in the simulation. Moreover, we can make the learning curve take a more sophisticated form such as S-shaped curves. In the current model, we use the learning curve that approaches the benchmark following an exponential curve because we multiply a constant to the difference between the focal firm and the benchmark firm. Finally, we can further investigate the interaction between the benchmark selection range parameters and the learning speed parameters. Combining variations in learning target and learning rate, we can draw response surfaces in the three-dimensional space similar to Park et al. (2012).

6.5.1 Practical Implications

The clustering and simulation framework proposed in this chapter mainly serve the purpose of researchers interested in understanding firm behavior types and ecosystem dynamics. These inquiries pertain to the ecosystem-level analytics. However, the managers of individual companies embedded in the ecosystem may be more interested in performing what-if and scenario-based analysis that generates direct insights on what strategic stances their companies should take. There are a few conceptual and technical challenges to extend the current simulation framework in order to serve the purpose of the managers of individual companies. The events that individual company managers are interested in are relatively minuscule compared to the entire ecosystem dynamics. Thus, simulation results generated from various scenarios may not yield significant variations in output analysis. Moreover, simulation studies require replications. Aggregating and visualizing a large number of replications from the perspective of a single firm is another technical challenge. Representing and visualizing simulation models and results are active research areas to date.

This chapter focuses on the formation process of interfirm relationships including alliance and M&A. In the real-world innovation landscape, most innovation activities and results are incremental to previous state-of-the-art technologies. However, disruptive innovation occasionally happens and it radically changes the competitive and technological landscape. Georgantzas and Katsamakas (2007) and Georgantzas (2011) use the system dynamics modeling approach to build a simulation-based and scenario-driven decision support framework. Their approach could potentially inform the development of the clustering and simulation framework proposed in this chapter. One difference is that our simulation approach inherently spans multiple levels of organizational interactions incorporating an array of simulation methods ranging from agent-based modeling and intra-firm process modeling to inter-organizational strategic and economic modeling.

From developing these clustering and simulation framework, we learned that data-driven approach to characterize firm strategies would have enormous potential to transform corporate and policy decision making processes. During the past decades, we have built a large body of normative thought framework for describing why and how firms behave in a certain way based on the game theory. Such an approach often lacks consideration of specific context that a company or an organization is embedded in. Our data-driven approach can fill the gap between the current strategic management literature and the reality of corporate decision making.

6.6 Conclusion

This chapter proposes a generative workflow using clustering and organizational simulation methods for understanding the relationship between organizational learning and ecosystem formation. The clustering algorithm identifies five distinct behavioral clusters and estimates transition matrices using the maximum likelihood estimator and the expectation maximization algorithm. The clustered profiles significant crossovers with predefined industry segments based on the SIC codes. The estimated transition matrices based on the observational data of interfirm alliances and M&A inform the simulation model that emulates the ICT ecosystem. The simulation model provides a framework to test the effect of organizational constructs—organizational learning in this chapter—on the system-level structure.

This chapter makes timely contributions at this time of data abundance and primacy. A methodological contribution lies in bridging data mining methods with simulation methods. So far, data mining and machine learning algorithms have grown significantly as empirical methodologies standalone. On the other hand, simulation has the advantage of giving a clear mental model for complex phenomena. We argue and demonstrate that connecting these two distinct methodologies can generate great synergy for decision-making and strategy planning practices. Another contribution is that we demonstrate a data-driven identification of industry structure without relying on predefined classification schemes. The SIC scheme is still serving its purpose by providing an exhaustive view over the economy, but it is too rigid to portray the fast-paced ICT ecosystem faithfully. Now that industry boundaries are blurred and distinction between competitors and collaborators is soften, a data-driven classification based on revealed behavioral patterns can greatly complement the traditional mental model of industry structure for the purpose of strategic planning.

The most promising aspect of the study presented in this chapter is the methodological richness. This chapter employs the model-based approach for both clustering and simulation, while previous chapters mostly rely on empirical methods. Thus, this methodology is highly extensible for other research subjects. For example, we can apply the same clustering algorithm to categorize new product development practices of different firms and build a simulation framework.

There are several directions to which we consider expanding this chapter. One immediate and foreseeable future work is to streamline the workflow between clustering and simulation. We run clustering and simulation separately in this chapter, although they are linked via manual curation. Streamlining these two steps allows automatic setup for simulation based on data mining results and will make this computational framework more accessible and adaptable to other settings. Furthermore, we can even implement a visual and interactive system once the workflow is integrated. Such a visual analytics system that promotes data-to-simulation process will become indispensable for scenario planning as data-driven decision-making is widespread. Lastly, we can modify the current simulation framework to test other organization theories beyond organizational learning.

CHAPTER VII

CONCLUSION

7.1 Summary

This dissertation starts with describing the network structure and the transformation trajectory of the ICT ecosystem using network visualization in Chapter 2. Sprinkled across five broad industry segments and 58 SIC codes is a myriad of companies that constitute the ICT ecosystem. Our network visualization approach vividly narrates the status quo of the ecosystem and its path of transformation over the past two decades. We show that the ICT ecosystem underwent a turbulent period around the year of 2000. This chapter operationalizes the concepts of coopetition, convergence, and complexity in visual terms by dichotomizing alliance relationship into cross-industry or within-industry.

Zooming in from a macroscopic portrait of the ICT ecosystem, we start relating interfirm relationship to technological innovation in new product offerings in Chapter 3. We particularly focus on the smartphone industry because of the special feature that smartphone as a product offers for our research. The functional value of a smartphone is fully realized only with the availability of capable operating systems. These days, operating systems serve as digital platforms bridging third-party application developers and users. Previous research on technology management studying how product innovation evolves over time largely relies on the search space model hinging on the concepts of the breadth and depth of search activities. Digital platforms are not present in the traditional models and this dissertation attempts to close the rift between the classical search space innovation model and the reality where products are increasingly enabled by various types of digital platforms.

Smartphone not only involves digital platforms but also requires network carriers in order to function properly. In the end, a smartphone is a phone before a hand-held computing device. Chapter 4 turns to the relationship between product device manufacturers and network service providers. In the mobile phone industry, service providers serve as a distribution channel for physical devices. Since it is unlikely for consumers to multihome network carriers, a service provider has the gate keeping power to its customer base. In this setting, sourcing a technologically superior product can be an effective way to leverage products to increase customer base from the service provider's perspective. We focus on the industry-wide sensational event of the introduction of the iPhone as a research setting. Using the difference-in-differences estimator, we show that service providers can implicitly solicit products with better technical specifications by introducing a strong product on its network and increasing competition among the manufacturers. In other words, manufacturers run as hard as possible to stay the same on the service provider's network. Furthermore, like other systems with self-sustaining feedback loop, this increased level of competition does not dissolve even after the original impetus is removed.

After looking at manufacturer-platform and manufacturer-service provider relationships and how these relationships coevolve with product innovation, we attempt to observe three firms side by side altogether in Chapter 5. The focus of this chapter is to quantify differential impact of new product introduction to each of three types of companies involved in the value creation process. Using multi-country event study, we identify strong positive financial implication of new product introduction for the manufacturer. The positive impact is amplified when the product is technologically superior to preexisting models. The stock price of companies assuming other roles such as service providers and platform developers seems generally insensitive to new product introduction and technical specifications. Contrasting between announcement and release events, we also show that the market is overexcited at announcement and disappointed after the actual release of the product. Our findings in this chapter suggest that better product does not necessarily benefits involved parties equally.

We then step back again to the macroscopic viewpoint in Chapter 6, where we model and infer firm behavior in forming relationships with others. In Chapter 2, firms are categorized into bins predefined by the standard industry classification scheme. We first cluster relationship-forming behavior by estimating transition matrix and interarrival time matrix with maximum likelihood estimator and expectation maximization. Using the identified clusters, we run organizational simulations informed by the organizational learning theory of adapting behavior.

These five chapters show the ICT ecosystem and in-depth analysis particularly around the smartphone industry with alternating macroscopic and microscopic lenses. We hope this line of research extends the thought framework on how to conceptualize the activities in the ICT ecosystem and furthers the understanding of the interaction between interfirm relationships and product innovation.

7.2 Generalizability to Other Business Ecosystems

Although the research context of this dissertation is the ICT ecosystem, our approach and methods employed in this study are readily applicable to other business ecosystem settings. To illustrate the generalizability of our approach, we take as examples two immediately related business ecosystems—the entrepreneurial ecosystem and the third-party application developer ecosystem. Both ecosystems are closely related to the ICT ecosystem and they have distinctive features different from the ICT ecosystem.

Let us first examine the differences of these example ecosystems from the ICT ecosystem, and then consider how our approach is relevant and generally applicable to these example ecosystems. While the ICT ecosystem contains large and established firms, the entrepreneurial ecosystem has de novo companies, angels, and venture capital investors. The relationship that a startup company seeks differs from the relationship that an established firm looks for. A startup company may need a series of funding, while an established firm searches for partners to jointly embark on a new project or a new market. The third-party application developer ecosystem differs from the ICT ecosystem in that it primarily focuses on the software development activities. The application developers are critically influenced by the strategic decisions of the platform companies and the success of the platforms is also greatly affected by the level of participation from the developer community. The platform companies and the application developer ecosystem are in a symbiotic relationship.

Despite these contrasts, researchers can use the approach and methods employed in this dissertation to study dynamics of these two adjacent ecosystems. Since ecosystems can be represented as a network, we can use the network visualization and quantification approach demonstrated in Chapter 2. For the entrepreneurial ecosystem network, nodes would represent not only de novo firms (portfolio companies) but also venture capitalists (investors) and individual entrepreneurs (people). Edges would mean relationships including investment, employment, and competition. Such a network can be modeled and visualized as a tripartite graph (Basole et al., 2015c). The application developer ecosystem network would contain companies and individual developers building third-party applications running on one of the digital platforms. In that case, edges would mean the platform choice of application developers.

The relationship formation behavioral patterns in both ecosystems can also be similarly modeled using the clustering and simulation framework shown in Chapter 6. For the entrepreneurial ecosystem, we can infer different types of de novo firms' strategy in terms of relationship formation, new product and service development, and achieving funding rounds. Based on the data-driven inferences of firm behaviors, we can develop another simulation framework that, for example, helps decision making on investment and acquisition. For the application developer ecosystem, the clustering method shed light on how developers launch and patch new and existing applications. The simulation approach may help understand the emergent interaction patterns between the platform companies and the application developer community.

This subsection argues for generalizability of our approach using example ecosystems that are closely connected to the ICT ecosystem. However, our methods and approaches can inform researchers interested the business ecosystems in other relatively distant fields such as supply networks in the automobile industry or hierarchical networks of financial institutions.

7.3 Future Opportunities

As we progress on the research presented in this dissertation, we realize that mix-and-match of methodology and research domain may yield several immediate future research opportunities extending our work. We provide a few examples of future research opportunities by applying a method used in one domain to another domain.

1. **Simulation for the search space with digital platforms**

   Chapter 3 theorizes how firms achieve an innovative solution in the technological search space and empirically investigates how the existence of digital platform interacts with the search process for innovation. Based on this empirical analysis, we can further solidify our proposed conceptualization of search space with digital platforms by formulating a constrained NK model. Initially inspired from biological evolution process, the NK model takes into account interaction among different technological dimensions. We can revise the model to be adapted to the digital platform era by imposing digital platforms as constraining factors that enables and disables a certain combination of technologies. Using a similar simulation approach used in Chapter 6, we can strengthen our newly proposed search space theory.

2. **Unsupervised clustering to identify product family based on technical specifications**

   Product family is currently defined by manufacturer-specified predecessor-successor relationship. Chapter 3 extends the definition of product family by incorporating the main CPU chipset and the internal project codename, but it is still a top-down approach. A complex product evolves in an organic way just like companies form relationship with each other seen in Chapter 6, so we should be able to identify time-series evolution of product family clusters using unsupervised clustering method used in Chapter 6. Similar to what Chapter 6 could replace the externally-imposed standard industry classification based on top-down approach, this data-driven identification of product family could inform the general evolution pattern of product technical specifications.

3. **Advanced visual analytics for cluster analysis and scenario explorer**

   Chapter 6 identifies the inherent community structure in interfirm alliance and M&A network. Although the chapter looks for clustered behavior for overall network, we can break down such behavioral clusters by time. Once time-varying clusters are identified, we can visualize the time-series changes in clusters using network visualization methods shown in Chapter 2. Using such a visual analytics system, we can allow decision makers to visually inspect how individual companies move along with the evolving industry ecosystem. Decision makers are also allowed to visually explore alternative scenarios when policy intervention is applied from the individual company perspective.

4. **Expanded investigation on broader ICT ecosystem**

   The working definition of the ICT ecosystem used in this dissertation usually involves corporations that are sufficiently large to form alliances or make acquisitions. Particularly, we focus on three types of companies: manufacturer, network service provider, and platform developer. The ecosystem definition has shifted to embrace not only large corporations playing different roles and dependent on each other but also small and peripheral players such as third-party application developers. The nature of interfirm relationship also moves from formal alliance and M&A to informal and casual relationship such as service linkage through APIs. Using the methodology of this dissertation, we can expand the subject of the investigation into a broader ICT ecosystem which will provide a more complete view on the ICT ecosystem. Moreover, we can apply our approach to other types of business ecosystems. Entrepreneurial ecosystems composed of start-up companies, venture capital investors, and talents are excellent exemplary contexts to apply our methodology for analysis.

We believe that data-driven business analytics from the ecosystem perspective continue to thrive for conceiving and developing better decision support systems. We hope this dissertation provides a guideline for such future endeavor.

APPENDIX A

SUPPLEMENTARY MATERIAL

A.1 Clustered Profile Transition Diagrams

This section contains a collection of clustered behavior profiles represented as transition diagrams from Chapter 6. Each figure contains three subfigures which show transition diagrams in three decomposed state spaces: main relationship type (alliance, joint ventures, full acquisition, partial acquisition, and portfolio investment), sub relationship type (strategy, R&D, marketing, technology transfer, manufacturing, and licensing), and border-segment type (within border within segment, within border cross segment, cross border within segment, cross border cross segment). Average time for each transition is in parenthesis next to the corresponding transition probability. Node abbreviations are as follows.

- LC: Left Censor, RC: Right Censor
- Alli: Alliance, JV: Joint Venture, Full: Full Acquisition, Prtl: Partial Acquisition, Inv: Portfolio Investment
- Strat: Strategy, R&D: R&D, Mkt: Marketing, Tech: Technology Transfer, Mfg: Manufacturing, Lic: Licensing
- WBWS: Within Border Within Segment, WBCS: Within Border Cross Segment, CBWS: Cross Border Within Segment, CBCS: Cross Border Cross Segment

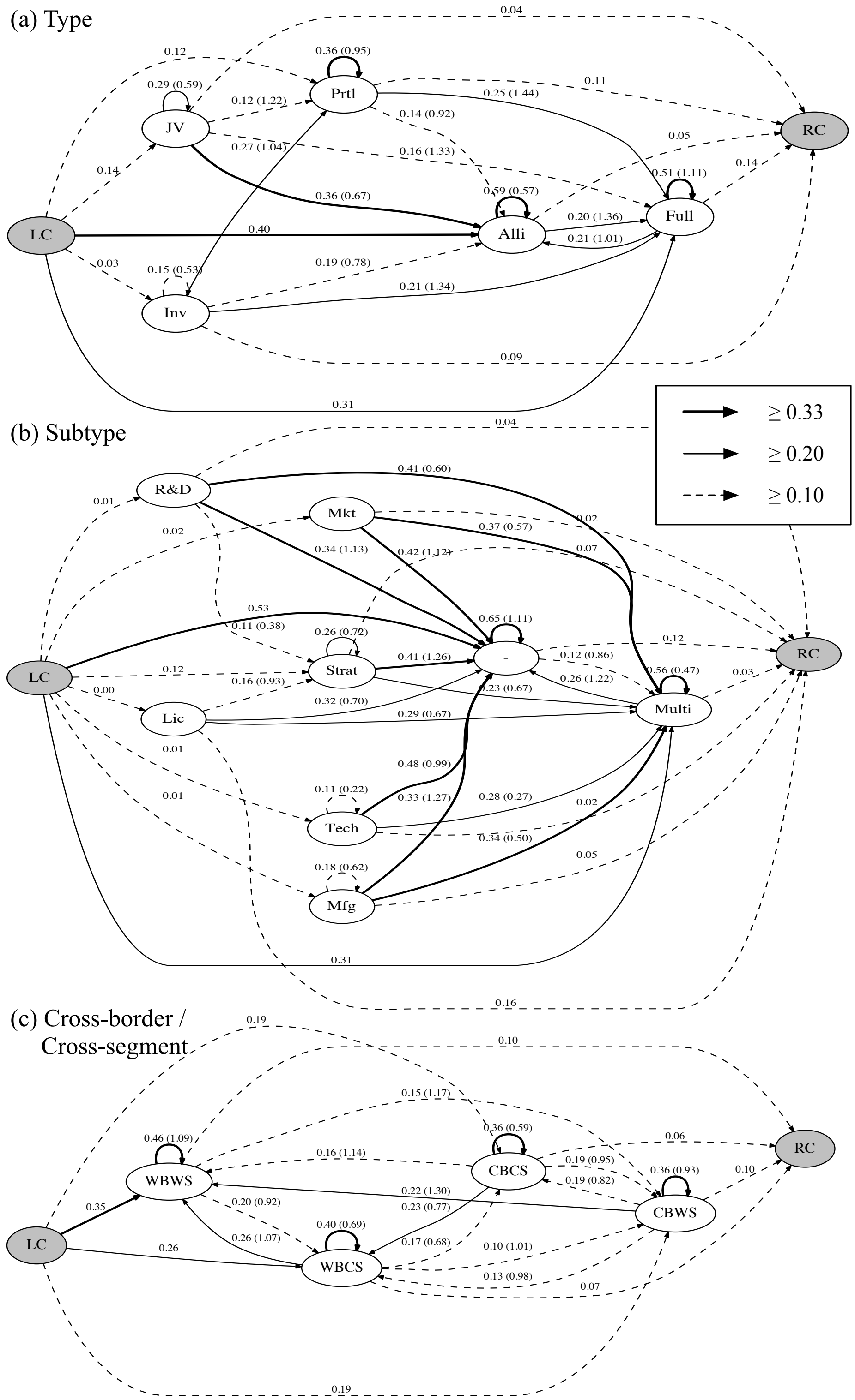


Figure 37: Clustered Strategy Profile 1

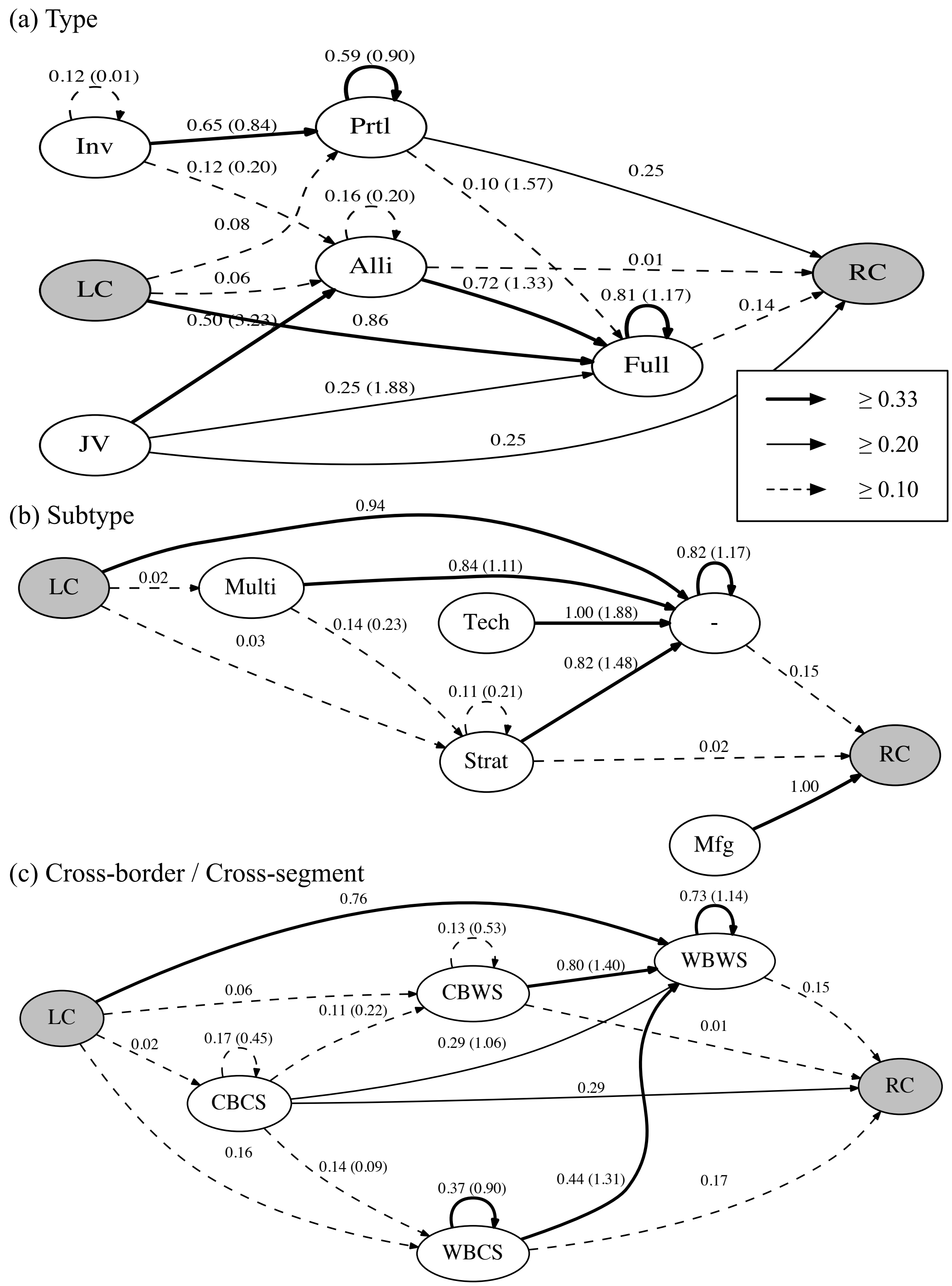


Figure 38: Clustered Strategy Profile 2

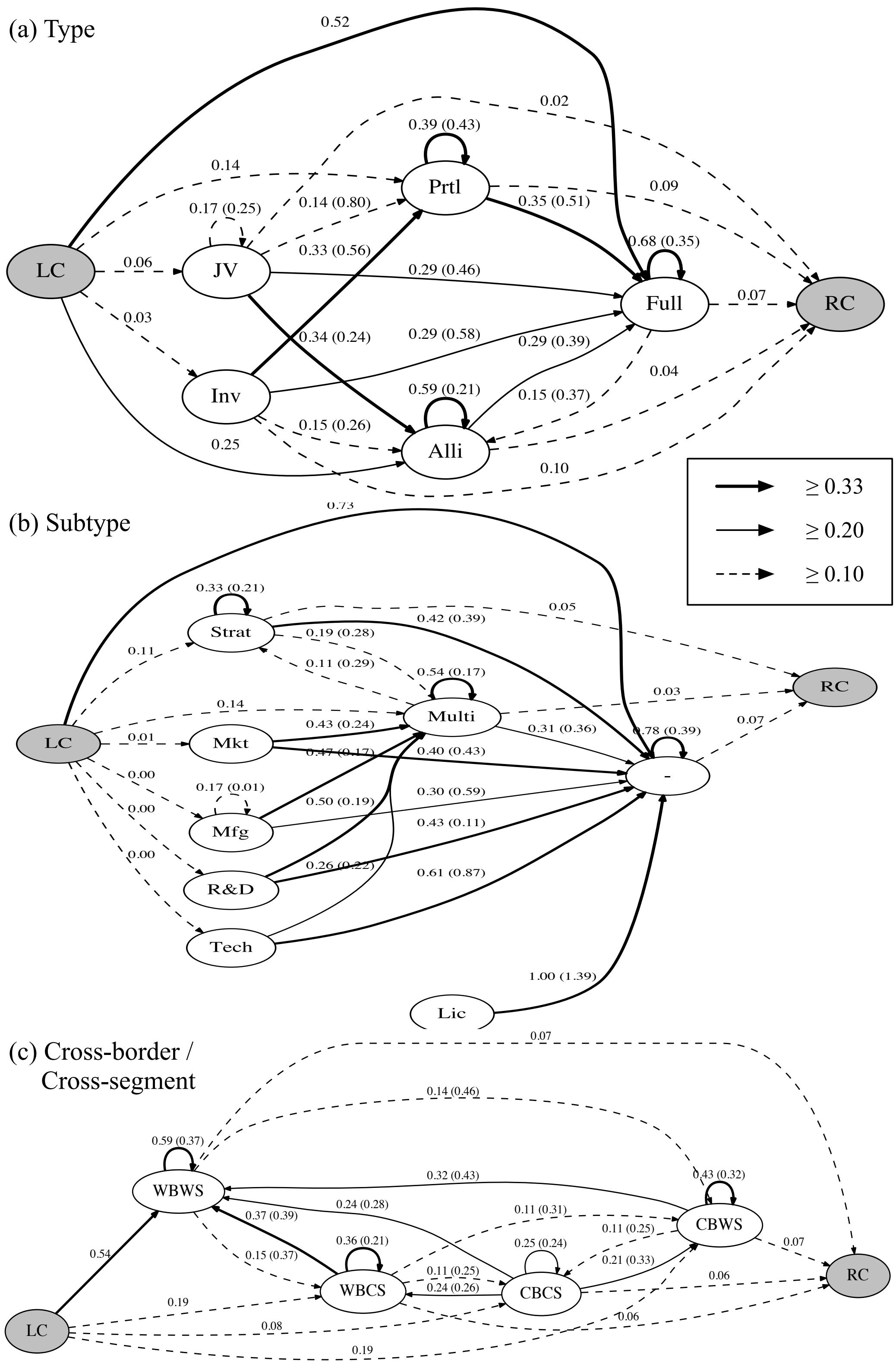


Figure 39: Clustered Strategy Profile 3

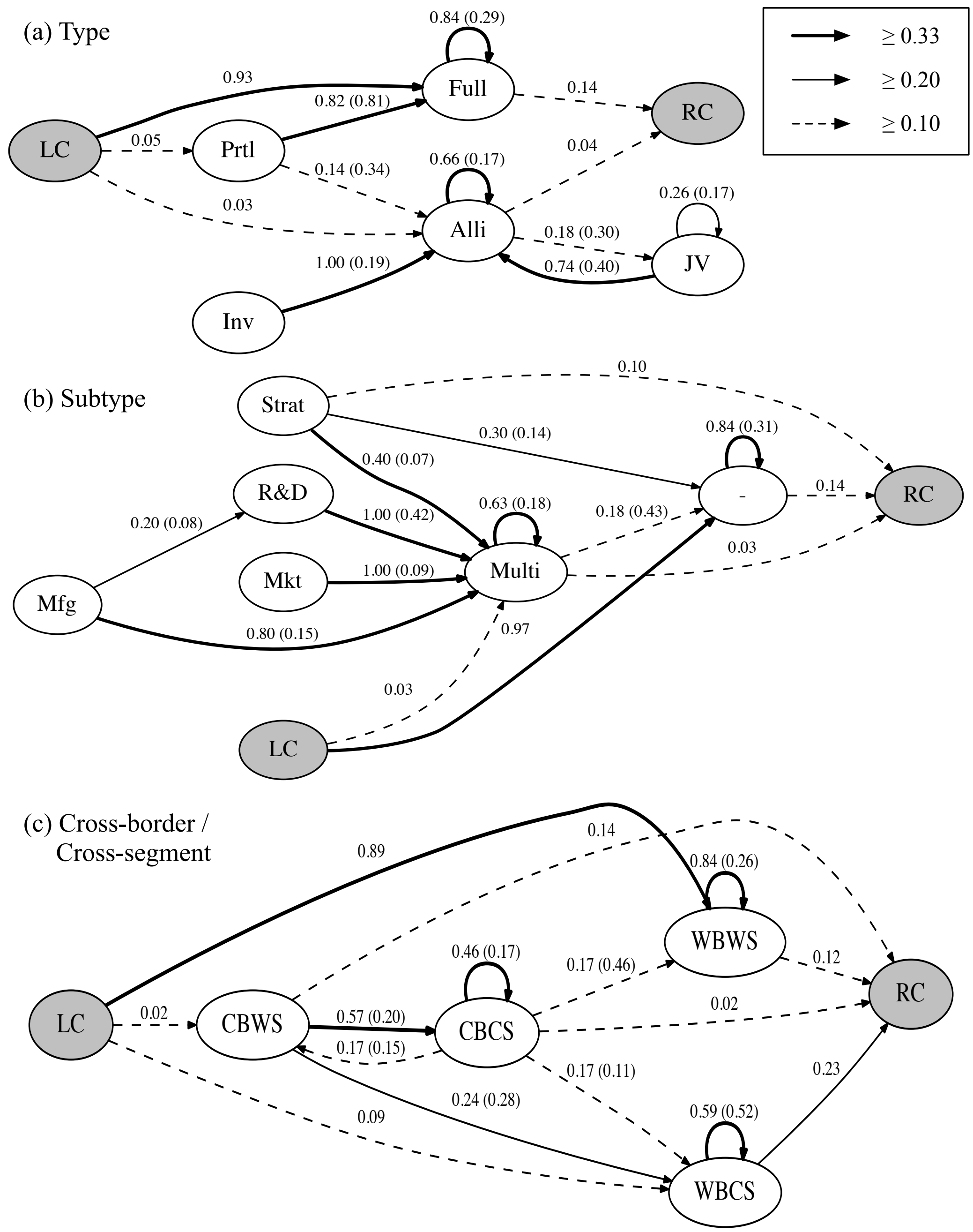


Figure 40: Clustered Strategy Profile 4

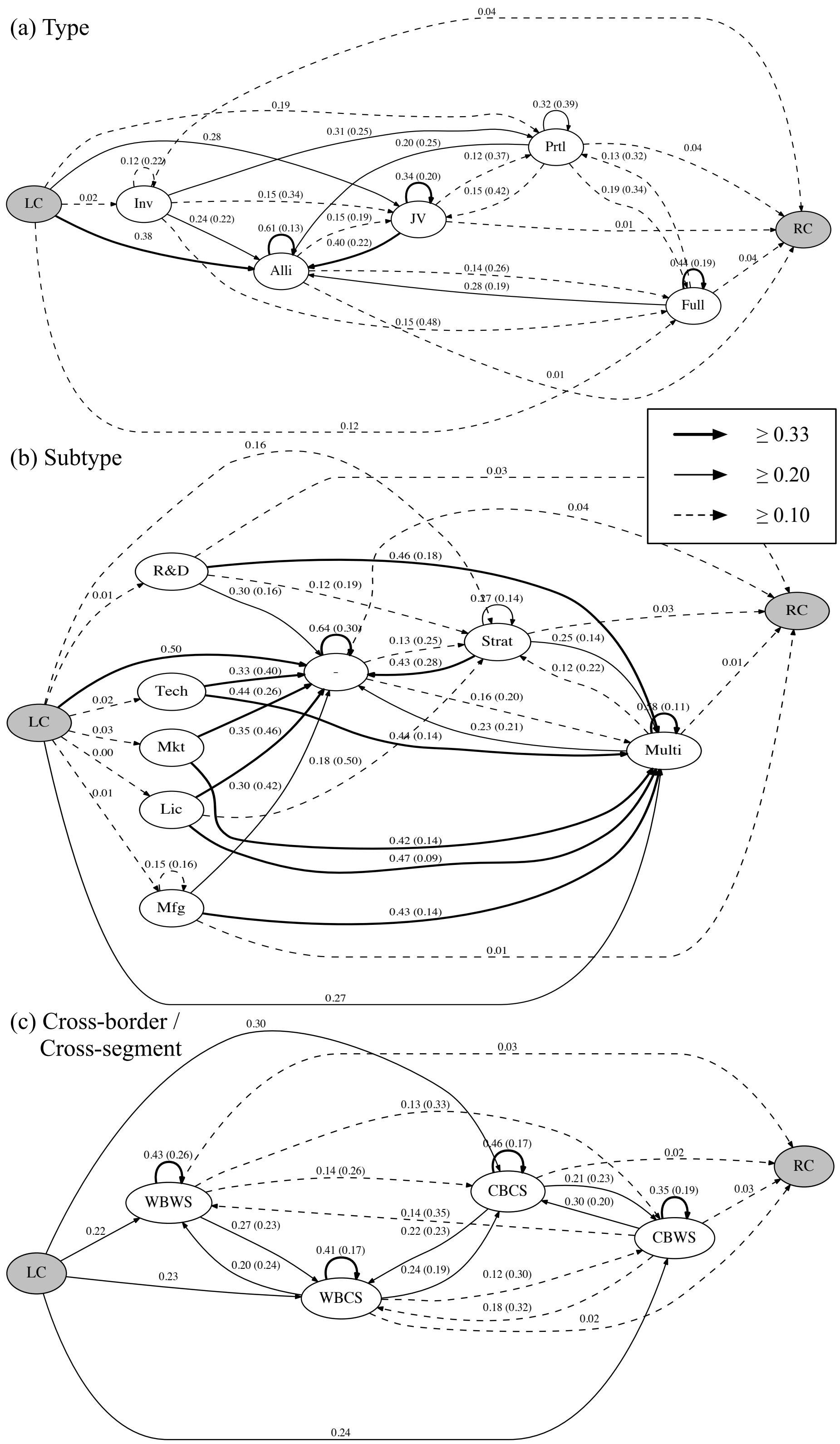


Figure 41: Clustered Strategy Profile 5

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